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Incorporating systems dynamics and spatial heterogeneity in integrated assessment of agricultural production systems

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ABSTRACT. Agricultural systems are complex and dynamic, being made up of interacting bio-physical and human sub-systems. Moreover, agricultural systems are remarkably diverse, both within geographic regions and across regions. Accordingly, this paper focuses on dynamics and heterogeneity in coupled, multi-disciplinary simulation models of agricultural systems. We begin with a discussion of the principal features of agricultural production systems. We then present an example of a 'loosely coupled' model, the type of model most researchers have used to represent agricultural systems. We discuss the loosely coupled model's features and limitations, and show how it can be modified to incorporate feedbacks among sub-models. Finally, we use a case study of a hillside production system in Ecuador to illustrate the importance of model coupling, dynamics and heterogeneity in the analysis of production systems. This example shows that feedbacks and threshold effects are most important at sites most vulnerable to tillage erosion.

Introduction

There is growing evidence that rural poverty and resource degradation are interrelated phenomena, both being the result of a complex set of physical, biological, and human systems. Each component system is complex, and needs to be understood before we can hope to understand the dynamics of the larger system. This paper reports on advances in modeling agricultural systems so that they can be used to assess agricultural sustainability and its role in poverty and resource degradation.

We begin with the view that agro-ecosystems are complex, dynamic systems with spatially and temporally varying inputs and outputs that

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are the result of interrelated physical, biological, and human decision-making processes (Antle *et al.*, 2001). This view is consistent with the rich literature on bio-economic models in which economic decisions of farmers, foresters, and fishers are modeled as economic optimization, subject to economic and bio-physical constraints. However, much of the literature focuses on stylized theoretical models that abstract from empirical details needed to understand and predict the behavior of these systems (for reviews of relevant literatures, see Sanchirico and Wilen, 1999; and Antle *et al.*, 2001). The complexity of these systems means that quantitative analysis of agricultural systems is required to generate information to support policy decision making or to address the issue of rural resource degradation and its linkages to poverty.

The contribution of this paper is to propose methods that can be used to implement the analysis of agricultural production systems as complex systems, and to investigate the properties of one such system to illustrate these methods. We begin with an example of the most widely used type of model that we describe as 'loosely coupled', we discuss this model's features and limitations, and show how the loosely coupled modeling approach can be modified to incorporate feedbacks among sub-models. Finally, we present a case study of hillside agriculture in Ecuador to illustrate the importance of model coupling, dynamics, and heterogeneity in the analysis of production systems. This case study shows that feedbacks and threshold effects are most important at sites most vulnerable to tillage erosion. In the concluding section we relate these findings to the broader challenges of modeling linkages between poverty and resource degradation.

Modular simulation models of agricultural systems

Our goal is to study the behavior of an agricultural system by simulating a model of the system under a set of specified bio-physical and behavioral conditions. To achieve this objective, the models describing the bio-physical and economic decision-making components of the systems must be able to communicate with each other on compatible spatial and temporal scales. The modeling strategy we propose is a modular one, in which disciplinary model components are developed so that they can interact through standard communications protocols, similar to the 'plug and play' concept used in modern software development. The modular approach typically maintains each disciplinary model in its original form, although simplified versions may also be used that are more computationally efficient. Typically, this approach is implemented by executing each model in turn, and by using a subset of state variables from one sub-system as inputs into another sub-system. Most models in the literature have been developed using this 'loose coupling' strategy (e.g., Kaiser *et al.*, 1993; Bouman *et al.*, 1996; Rappoldt and van Kraalingen, 1996; Alig *et al.*, 1997; Shepherd and Soule, 1998). To illustrate, figure 1 presents a stylized example of an economic decision model and a crop ecosystem model. In a loosely coupled model, outcomes from one model are used as inputs into another model, but processes within each model are not linked.

The modular model-coupling approach has several advantages. First, it is adaptable to different production systems, and allows different researchers

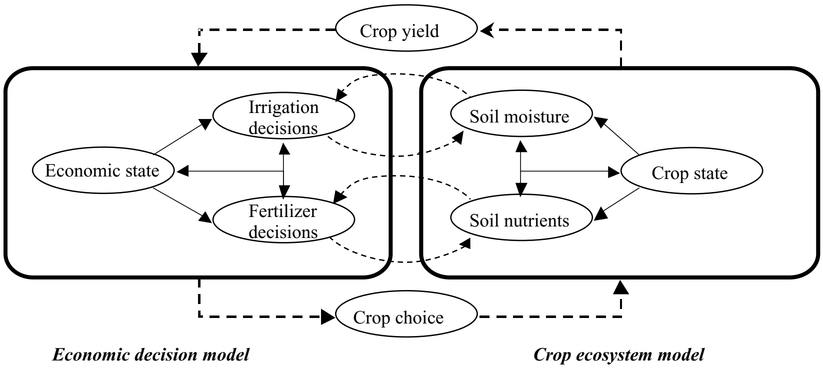

Figure 1. *Examples of loose coupling (heavy dashed lines) and close coupling (light dashed lines) of economic decision models and crop ecosystem models*

to develop different components for different applications independently. A key element that has been lacking in efforts to model coupled biophysical and economic systems is a set of data standards for communication between models. With data standards for inputs and outputs, data exchange and replication of results are possible at relatively low cost. This can be illustrated by the data standards for crop growth simulation models as developed by the International Consortium for Agricultural Systems Analysis for the DSSAT family of crop growth models (Hunt *et al.*, 2000). In the modular modeling approach described below, the DSSAT data standards for crop models are utilized along with a set of data standards for economic models. Second, the modular approach leads to improved transparency of models and it is easier for researchers to test models and replicate results. A common problem with many models is that they are large, complicated, and poorly documented 'black boxes', and consequently few if any researchers beyond the developers are able to use them. A third advantage of the modular approach is that it provides the capability to represent each disciplinary component of the system, including key features such as non-linearities and discontinuities, at the level of detail deemed suitable for each type of process. One of the alternative approaches is to utilize systems of reduced-form equations to represent a 'response surface' for a complex system (Morgan and Henrion, 1992). A disadvantage of the reduced-form approach is that it may fail to represent important non-linearities and other features outside the range of behavior represented in the simulations used to parameterize the reduced form.

One downside of the modular approach is that it may limit the ability to couple processes in the disciplinary sub-models of a system. One of our goals is to assess the effects of loose coupling on model behavior.

Implementing the modular approach with the Tradeoff Analysis software

In this section we outline how we have implemented the modular modeling approach using the Tradeoff Analysis (TOA) software (Stoorvogel *et al.*, 2001, 2004). Version 3 of the Tradeoff Analysis software (TOA3) is designed to analyze economic and environmental tradeoffs in agricultural production systems. The TOA3 implements the concept of loose coupling of disciplinary models; that is, each disciplinary model is executed independently, and outputs of one model are used as inputs into another disciplinary model. Also, in this system there are no dynamic feedbacks between disciplinary models. The TOA3 structure is presented in figure 2.

Two types of bio-physical simulation model are used in TOA3, crop growth models (specifically, models from the Decision Support System for Agrotechnology Transfer or DSSAT; Jones *et al.*, 1998) using the ICASA input and output format (see Hunt *et al.*, 2000) and environmental process models such as LEACHM (Wagenet and Hutson, 1986), WEPP (Water Erosion Prediction Project, 2004), Century (Parton *et al.*, 1994), and NUTMON (Nutrient Monitoring for Tropical Farming Systems, 2004). First, the crop models are used to characterize spatial variability in productivity across sites, as discussed in further detail below. Second, outputs from the econometric-process simulation model (land use, input use) are passed to environmental process models to simulate environmental impacts of management decisions. The TOA3 system documentation and example applications are available at *www.tradeoffs.nl*.

Econometric-process simulation models

The TOA3 software is designed to implement econometric-process simulation models (Antle and Capalbo, 2001). The econometric-process approach represents economic decisions on a site-specific basis, at spatial and temporal scales compatible with bio-physical crop simulation models and environmental process models, so that the bio-physical and economic models can be coupled at compatible spatial and temporal scales. In the econometric-process approach, farmers make discrete land-use decisions for each management unit (i.e., each parcel of land), and, given their land-use decisions, farmers make continuous input decisions for variable inputs (e.g., labor, fertilizer application rates).

To illustrate the econometric-process model approach, we consider a general production problem in which each producer makes management decisions on a land unit indexed by s. This land unit could be an individual field, a set of fields, or a whole farm, or even a collection of farms; the distinguishing feature is that the same management decisions will be applied to the entire land unit. Management decisions for this land unit are made for a specified decision period indexed by t, which typically would be a growing season or multiple growing seasons. Each decision period, the farmer has to choose between a finite, discrete set of activities indexed by a. For example, the farmer could be making the relatively short-run choice among alternative crops within an already determined crop rotation, or the farmer could be making the longer-run choice of a production system and the associated fixed capital. Each activity returns a value $v(p, \mathbf{w}, \mathbf{z}, \mathbf{e})$ where p is an output price, $\mathbf{w}$ is a vector of variable input prices (hired labor, fertilizer, etc.), $\mathbf{z}$ is a vector of fixed human and physical capital and any other fixed factors affecting production (family labor, animal and mechanical assets, other physical assets, size of the land unit, etc.), and $\mathbf{e}$ is a vector of bio-physical characteristics of the site. Here we will interpret this value function as expected net returns, but more generally it may be expected utility of income or wealth, or some other objective function. We define $\delta_{ast} = 1$ if the ath activity is selected on land unit s for period t and equal to zero otherwise. The farmer then chooses the activity that maximizes value

$$\max_{\{\delta_{ast}\}} \sum_{a} v(p_{ast}, \mathbf{w}_{ast}, \mathbf{z}_{ast}, \mathbf{e}_{st}) \tag{1}$$

The solution to this problem takes the form of a discrete step function

$$\delta^*_{ast} = \delta_a(\mathbf{p}_{st}, \mathbf{w}_{st}, \mathbf{z}_{st}, \mathbf{e}_{st}) \tag{2}$$

where $\mathbf{p}_{st}$ is a vector of the expected output prices and the other vectors are defined similarly.

Assuming the value functions are expected profit functions, using Hotelling's lemma the corresponding output supply function and the ith input demand function are given by

$$q_{ast} = \delta^*_{ast}\partial v(p_{ast}, \mathbf{w}_{ast}, \mathbf{z}_{ast}, \mathbf{e}_{st})/\partial p_{ast} \tag{3}$$

$$x_{iast} = -\delta^*_{ast}\partial v(p_{ast}, \mathbf{w}_{ast}, \mathbf{z}_{ast}, \mathbf{e}_{st})/\partial w_{iast} \tag{4}$$

Antle and Capalbo (2001) show how this theoretical decision-making framework can be transformed into a stochastic simulation model, by specifying systems of supply functions and factor demand functions (empirical analogs of equations (3) and (4)) that can be estimated econometrically and then used to simulate the discrete choice of activity (equation 2) and the input use decision and supply decisions. The input demand equations could be derived from either a conventional static problem, such as single-period profit maximization, or from a dynamic, intra-seasonal problem, such as the one discussed by Antle *et al.* (1994). Risk can be incorporated formally into this type of model as well (Antle and Capalbo, 2002).

Using bio-physical models to simulate spatial variability in productivity

An important feature of the TOA3 system is the loose coupling of bio-physical crop and livestock models with econometric production models. This linkage is designed to address a problem that has long plagued empirical production economics research; namely, how to 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 that is embedded in crop and livestock simulation models. Process-based models are particularly important for simulating out-of-sample phenomena, such as climate change or adoption of new technologies and management practices.

Production economists often specify production functions in the general form $q = f(\mathbf{x}, \mathbf{z}, \mathbf{e})$, where $\mathbf{x}$ is a vector of variable inputs, $\mathbf{z}$ is a vector of fixed inputs, and $\mathbf{e}$ is a vector of bio-physical factors. In practice the bio-physical factors $\mathbf{e}$ are represented in econometric production models by using *ad hoc* indicators of soil quality and climate such as dummy variables for soil types and average rainfall during the growing season.

The TOA3 software provides the capability to take an alternative approach to econometric modeling that exploits the scientific knowledge embodied in bio-physical process models. 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. Crop growth simulation models can be represented in stylized form as $q = g(\mathbf{x}, \mathbf{e})$. Defining average or expected input use in the population as $\mathbf{x}^*$, we can use the crop growth simulation to calculate a yield q^* for a specific location on the basis of soil and weather data as $q^* = g(\mathbf{x}^*, \mathbf{e})$. Stoorvogel *et al.* (2001) 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 the farmer knows about the productivity of the site based on its soils and climate. As an alternative to the general model $q = f(\mathbf{x}, \mathbf{z}, \mathbf{e})$, we can specify the production function $q = h(\mathbf{x}, \mathbf{z}, q^*)$. Substituting for q^* we obtain $q = h(\mathbf{x}, \mathbf{z}, g(\mathbf{x}^*, \mathbf{e}))$, showing that this procedure yields a special case of the production function $q = f(\mathbf{x}, \mathbf{z}, \mathbf{e})$ in which the bio-physical variables $\mathbf{e}$ are weakly separable from the variable and fixed inputs $\mathbf{x}$ and $\mathbf{z}$. In this way we use the bio-physical crop models to systematically transform site-specific bio-physical data into an estimate of the spatial or temporal variation in inherent productivity, and then use this variation in productivity to help explain observed behavior. This form of the production function implies that the behavioral equations (2), (3), and (4) depend on inherent productivity.

This linkage from crop models to economic models represents an example of loose coupling without feedback: the output of the crop model (crop yield) is used as an input into the economic simulation model to represent spatial variation in productivity. However, in the TOA3 software, there is no mechanism for management decisions taken by farmers to feedback to the estimated inherent productivity derived from the crop models. This limitation is discussed further in the following example.

Loose coupling example: Tradeoff Analysis of Ecuador's potato-pasture system

We now illustrate the loosely coupled model using a study of economic, environmental, and human health tradeoffs in Ecuador's potato-pasture production system (Crissman *et al.*, 1998). This study utilized a detailed econometric-process model of the potato production system with intra-seasonal dynamics of pest management decision making, and with inter-seasonal dynamics associated with the potato-pasture crop rotation. The original study also included a pesticide leaching component and a human health component. Subsequent research showed that erosion associated with tillage on steeply sloped hillsides was also likely to be a significant environmental and productivity issue, so that component was added (Veen, 1999; Hoogerwerf, 2002). Here, we will focus on the economic and environmental processes, recognizing that the health model component could be added. We will also abstract from the intra-seasonal dynamics of the original model, and focus on the inter-seasonal dynamics of the crop rotation.

Carchi Province in northern Ecuador is typical of the northern humid páramo Andes. The agricultural system on the steep Andean hillsides is dominated by the production of potatoes and milk. The research focused on two watersheds corresponding to the San Gabriel and Chitan rivers encompassing a total area of 95 km^2 ranging in altitude between 2,700 and 3,800 m above sea level. Being located close to the equator there is virtually no change in average monthly temperature ranging from 9 to 12°C. Average rainfall varies between 950 to 1300 mm/yr with significant year-to-year variation. Volcanic ash soils with their typical thick, black A-horizon, high organic matter content and high infiltration capacity have developed in relatively young volcanic ash deposits. Crissman *et al.* (1998) give a full description of the Carchi study site.

Here we focus on the spatial and temporal behavior of the economic and environmental properties of the potato-pasture system. The key indicators of the status of the system will be farm income, water quality, and sustaining productivity of the system. Farmers choose to produce potatoes, a high-value crop, but to do so they must use large quantities of potentially hazardous pesticides (insecticides and fungicides) on steeply sloped hillsides. The activities of preparing fields, planting and managing the potato crop, and harvesting, lead to soil being displaced down the steeply sloped hillsides (tillage erosion). The result is that topsoil becomes progressively thinner on the upper sections of each field, and accumulates in the lower section of each field. Because this area has deep volcanic soils, the accumulation on the lower part of the field does not raise productivity, but the loss on the upper part of the field lowers productivity when the topsoil reaches a critical depth, as illustrated in figure 3. As topsoil becomes thinner, larger quantities of pesticides leach below the topsoil layer and are transported into ground water and into down-slope surface water.

The economic problem faced by the farmer is to choose which crop to grow, potato (p) or pasture for grazing (g) each period on each field, given what was grown in the previous period. Farmers generally grow potatoes for two six-month periods, and then rotate them with pasture, to control diseases and pests, particularly the soil insect pest commonly known as the Andean weevil. If farmers knew that potato production also led to soil erosion and lost future productivity, they would have an incentive to choose the crop rotation that maximized the present value of present and future production. However, for the moment we assume either farmers are myopic or they are not aware of the long-term impacts of crop choice on productivity, as might be the case when erosion impacts productivity only after soil depth crosses a critical threshold as in figure 3, and thus base decisions on current-period expected returns. We assume expected returns from each activity in period t are $v(p_{ast}, \mathbf{w}_{ast}, \mathbf{z}_{ast}, \delta_{st\text{-}1}, q_a(\mathbf{e}_{s0}))$, for $a = [p, g]$. Here the term $\delta_{st\text{-}1}$ represents the effect of previous crop choice, and $q_a(\mathbf{e}_{s0})$ represents the inherent or expected productivity of the field, given baseline site characteristics $\mathbf{e}_{s0}$. The single-period choice problem is

$$\begin{aligned}\max_{\delta_{st}} v_{st} &= \delta_{st} v(p_{pst}, \mathbf{w}_{pst}, \mathbf{z}_{pst}, \delta_{st\text{-}1}, q_p(\mathbf{e}_{s0})) \\ &\quad + (1 - \delta_{st}) v(p_{gst}, \mathbf{w}_{gst}, \mathbf{z}_{gst}, \delta_{st\text{-}1}, q_g(\mathbf{e}_{s0})) \end{aligned} \tag{5}$$

The solution to the crop choice is $\delta_{st} = \delta(p_{pst}, \mathbf{w}_{pst}, \mathbf{z}_{pst}, q_p(\mathbf{e}_{s0}), p_{gst}, \mathbf{w}_{gst}, \mathbf{z}_{gst}, q_g(\mathbf{e}_{s0}), \delta_{st\text{-}1})$. Corresponding to the crop choice is the pesticide input

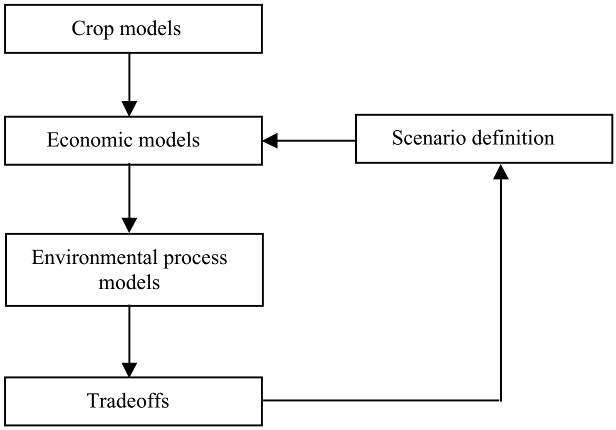

Figure 2. *The structure of the Tradeoff Analysis Model V.3*

decision $x_{pst} = -\,\partial v(p_{pst}, \mathbf{w}_{pst}, \mathbf{z}_{pst}, \delta_{st\text{-}1}, q_p^*)/\partial w_{pst}$ if the crop chosen is potato, and is $x_{pst} = 0$ if the crop choice is pasture. To simplify, we represent pesticide use as a single application, although the simulation model actually uses a system of dynamic factor demand equations to represent multiple, sequential applications of pesticides as described in Antle *et al.* (1994).

Two models are used to simulate environmental processes in this analysis. The first is a leaching model that translates the quantity of pesticide applied into a quantity leached below the crop root zone. In a highly stylized form, this model can be written as estimating the fraction leached as $\lambda_{st} = \lambda(\mathbf{e}_{st})$, so that the total quantity leached can be calculated as $L_{st} = \lambda_{st}\, x_{pst}$. The second environmental model expresses the difference in topsoil depth (in centimeters) between the upper and lower part of the field as a result of tillage erosion as a function of site characteristics (e.g., soil depth at the beginning of the production period, soil type, slope, climate) and management practices (in this case, which crop is grown). Thus tillage erosion can be expressed as $\varepsilon_{st} = \varepsilon(\mathbf{e}_{st}, \delta_{st\text{-}1})$. Included in the vector $\mathbf{e}_{st}$ of site characteristics is the amount of tillage erosion as a function of the cumulated past soil losses, thus $\mathbf{e}_{st}(\varepsilon_{st\text{-}1} + \varepsilon_{st\text{-}2} + \ldots)$.

To summarize, the loosely coupled model without feedback is comprised of the following system of equations

$$q_p^* = q_p(\mathbf{e}_{s0}), q_g^* = q_g(\mathbf{e}_{s0}) \tag{6}$$

$$\delta_{st} = \delta(p_{pst}, \mathbf{w}_{pst}, \mathbf{z}_{pst}, q_p^*, p_{gst}, \mathbf{w}_{gst}, \mathbf{z}_{gst}, q_g^*, \delta_{st\text{-}1}) \tag{7}$$

$$x_{pst} = -\delta_{st}\,\partial v(p_{pst}, \mathbf{w}_{pst}, \mathbf{z}_{pst}, \delta_{st\text{-}1}, q_p^*)/\partial w_{pst} \tag{8}$$

$$L_{st} = \lambda(\mathbf{e}_{st})x_{pst} \tag{9}$$

$$\varepsilon_{st} = \varepsilon(\mathbf{e}_{st}(\varepsilon_{st\text{-}1} + \varepsilon_{st\text{-}2} + \ldots), \delta_{st\text{-}1}) \tag{10}$$

Because the system is loosely coupled, it can be simulated recursively in the order indicated in figure 2: first, the crop models are simulated for each crop

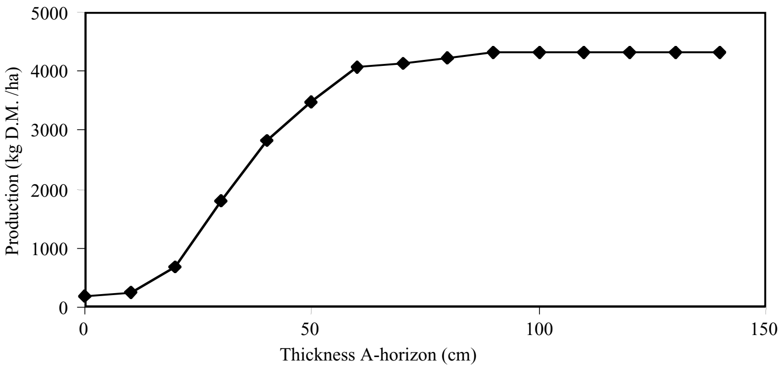

Figure 3. *The effect of differences in the thickness of the fertile A-horizon on the dry matter production of potatoes as simulated with DSSAT*

and site to produce the estimates of inherent productivity (equation (6)); second, the crop choice and input use decisions (7) and (8) are simulated over whatever time horizon is chosen by the analyst, using the inherent productivities as inputs; third, the leaching (9) and erosion (10) outcomes are simulated, using the sequences of crop choice and input use derived from equations (7) and (8).

Loose coupling and feedback

The model presented in the preceding section (equations (6)–(10)) is based on the assumption that land use and input decisions are based on the farmer's estimation of site-specific productivities, and *these inherent productivities do not change over time in response to soil erosion.* As we noted earlier, this assumption might indeed make sense when productivity exhibits a threshold with respect to soil depth, as in figure 3. Nevertheless, even without foresight, farmers are likely to observe that erosion is impacting productivity, thus soil erosion's impacts on productivity are likely to feedback to management decisions. Moreover, it is also possible that, as farmers begin to understand the dynamics of the production system, they will begin to anticipate impacts of their current decisions on future productivity and future expected economic returns; that is, they will begin to exhibit foresight. We now consider these two cases in greater detail.

Feedback without foresight

In this case the farmer's decision problem has the same structure as before, with the simple modification of the model by replacing equation (6) with

$$q_p^* = q_p(\mathbf{e}_{st\text{-}1}), q_g^* = q_g(\mathbf{e}_{st\text{-}1}) \tag{6'}$$

Thus, in each period the farmer's estimation of inherent productivity of each crop at each site is a function of the actual site conditions, including soil depth. It is now possible to simulate the system in the same sequence as described in the previous case of loose coupling without feedback, *except that this sequence must be followed for each time step*. However, the system remains loosely coupled in the sense that each model can be operated independently of the others, in the specified sequence, using only the appropriate outputs from one model as inputs into another model.

Feedback with foresight

Suppose a farmer has a rolling time horizon of T growing seasons. Given knowledge of the dynamics of the system, the farmer chooses the sequence of crops (i.e., the crop rotation) expected to maximize the present discounted value of the system for these T growing seasons. Thus, following equation (5), each period the farmer solves the problem

$$\max_{\{\delta_{st}\}} \sum_{t=1}^{T} v_{st}/(1+r)^t \tag{5$'$}$$

Each period the farmer implements the current-period optimal decision, conditional on expected future decisions. This problem can be solved using the well-known Bellman method. To simplify, we assume that the farmer considers two management options, either to continue the conventional potato-pasture crop rotation (i.e., two seasons of potato followed by two seasons of pasture) or to switch to permanent pasture. To implement this model, the farmer must form expectations about the future path of soils and productivity (as well as prices). Expectations about future productivity can be estimated by running the erosion model (10) over a given time horizon, assuming typical management of each system, and then using that sequence of soils to simulate the crop, economic, and leaching models (equations 6′, 7, 8, 9) using the procedure for the loosely coupled model with feedback. After performing this for one time period, time is advanced one period, and the sequence is repeated. In each time step the soil simulation is initialized with values from the previous period.

Close coupling

Processes in the sub-models of a complex coupled system typically operate on various time steps. For example, daily or even shorter time steps are used in many bio-physical crop growth models, whereas some other crop ecosystem models such as the Century model operate on a monthly time step. While most economic models use a single seasonal or annual time step, some economic models incorporate intra-seasonal sequential decision making and operate on time steps determined by management operations, such as planting, applying fertilizers and pesticides, and harvest (Antle and Hatchett, 1986; Antle *et al.*, 1994). When researchers design a system of coupled sub-models, they must decide what time step will be used for the communication of information between sub-models. In order to model the dynamic interactions between bio-physical processes, such as climate and pest population dynamics and decision-making processes such as pest management, the crop growth and pest population sub-models would need to interact with the economic decision-making sub-model on a time step much shorter than the whole growing season, perhaps on a daily basis.[1] This is the situation when models will need to be closely coupled.

Recall that the concept of inherent productivity utilized in the loosely coupled model was based on the assumption that inherent productivity was calculated for an average input vector x^*. One way to introduce a closer coupling of crop growth and economic simulation models in the system of equations (6)–(10) is to specify that inherent productivity (equation (6) or (6′)) depends on the current, site-specific management decisions, such as pesticide or fertilizer use. Under this specification, the system of equations (6), (7), and (8) is simultaneous in the input vector. While it is beyond the scope of this paper to discuss the use of closely coupled models in detail, we observe that at least two strategies are available. One approach is to decompose each of the models into a sequence of sub-processes that can be loosely coupled. Once that has been achieved, the loose coupling with feedback approach can be applied. Another approach is to simulate the two models sequentially, once for each of the shorter time steps, each time using data from one model to initialize the other model up to that point in time.

Application: the Ecuador potato–pasture system

TOA3 was applied to study the potato–pasture system in Carchi province described above. The setup of TOA3 is that the different models are loosely coupled, i.e. the models run sequentially and the output of one model is the input of the next model. The process is illustrated in figure 4 with actual model results. A range of different models are available for the area, including calibrated crop growth simulation models (Bowen *et al.*, 1999), an economic simulation model based on a two-year dynamic farm survey (Crissman *et al.*, 1998), a calibrated model for the estimation of pesticide leaching (Stoorvogel *et al.*, 2003), and a statistical model for the estimation of tillage erosion (Veen, 1999; Dercon, 2001).

Figure 4 follows the structure of figure 2. First the inherent productivity is calculated using the crop growth simulation models (equation (6)) on the basis of soil and climatic variability and average crop management as observed in the farm survey. The inherent productivities are then input into the economic simulation model. In this example, the economic simulation model simulates crop choice (equation (7)) and input use (equation (8)). Crop choice and input use can then be used in combination with the environmental characteristics to simulate pesticide leaching (equation (9)) and tillage erosion (equation (10)). The analysis finally leads to the construction of the tradeoff curve between, for example, pesticide leaching and tillage erosion. Tradeoff curves are typically constructed by varying parameters in the production system that affect the economic incentives perceived by farmers in their land-use and input-use decisions. As farmers respond to changing economic incentives through changes in land use and input use, the sustainability properties of the production systems change. For example, in the potato–pasture production system, as potato

[1] But also note that when processes do not interact directly but can be characterized through the loose-coupling approach, each sub-model can operate on its own independent time step.

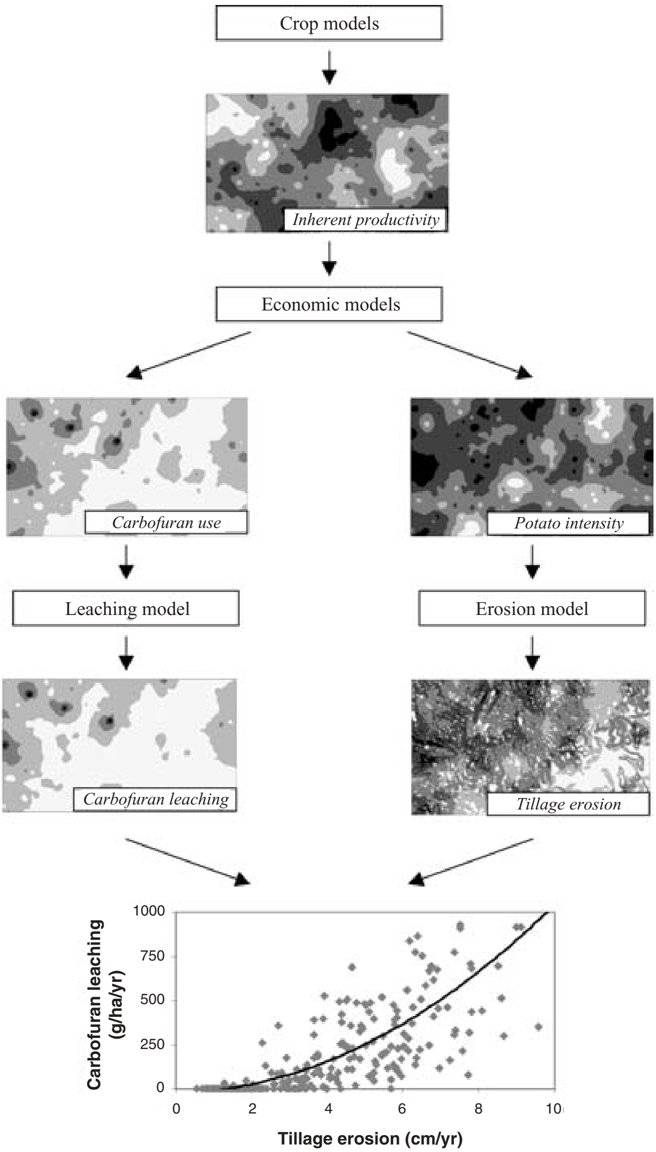

Figure 4. *An example from the Carchi study area with loosely coupled models (In the maps darker colors represent high values for inherent productivity, carbofuran use and leaching, potato intensity in the rotation and tillage erosion)*

prices increase relative to milk, farmers shift land use towards potato production, and also apply more inputs linked to potato management. The effect of these behavioral changes is increased pesticide use and the environmental and human health effects associated with pesticide use. In this paper, we focus on the potential environmental impacts of the system.

Figure 4 shows graphically how erosion and leaching outcomes are derived using the loosely coupled system, where the tradeoff between these outcomes is generated by varying the potato prices. Alternative policy, technology, and resource change scenarios can also be evaluated.

Feedback without foresight

Tillage erosion and pesticide leaching have very different effects on the agricultural production systems in the region. Tillage erosion directly affects the production system through a reduced future productivity, particularly for potatoes. However, pesticide leaching has off-farm effects in terms of contamination of ground and surface waters but does not influence the productivity of the system. This means that, if we talk about feedback effects, tillage erosion will be the dominating process that results in feedbacks and in changes in the inherent productivity. We should note that these feedbacks result in production changes but also in changes in pesticide leaching. The example illustrates the importance of feedbacks and the limitations of using the previously described loosely coupled models without feedbacks.

As we noted earlier, the model also exhibits threshold effects due to the relationship between productivity and soil depth (figure 3). Soil depth also is importantly related to leaching. The spatial correlations between features, such as slope and depth of the A horizon, on the one hand, and tillage erosion, on the other hand, will jointly determine the extent of productivity loss and leaching.

The model was run for 30 cropping cycles with a fixed inherent productivity. Afterwards tillage erosion was modeled and the effects of changes in soil properties were evaluated in terms of inherent productivity and pesticide leaching. The average inherent productivity for potatoes was 5,600 kg dry weight per ha per year. Potatoes were grown six out of ten years, average tillage erosion was 1.8 cm per year and carbofuran leaching was 254 g per ha per year. The results are indicated in figure 5 and referred to as the base run. Next we assessed the effects of tillage erosion rates on inherent productivity and pesticide leaching without feedbacks. Over the 30-year time period, tillage erosion would result, on average, in a 4.6 per cent decrease in inherent productivity due to the decline in topsoil in the upper parts of the fields. The impacts on leaching were much more important. As the topsoil was removed, leaching increased by 40 per cent, on average, over the 30-year time horizon.

The bottom of figure 4 shows the results of this analysis in terms of leaching and erosion outcomes. Each point in the figure is an average outcome for the watershed derived from replications of the stochastic models under a range of different output prices. The line fitted through these points shows that there is a tendency for leaching to increase faster than erosion, indicating a non-linearity in these relationships in space. At low levels of erosion, there is little if any leaching. As erosion increases, the chance of a high rate of leaching increases. This behavior is consistent with the threshold phenomenon discussed earlier.

The economic simulation model shows that changes in inherent productivity feed back to the farmer's choice of crop and inputs. This

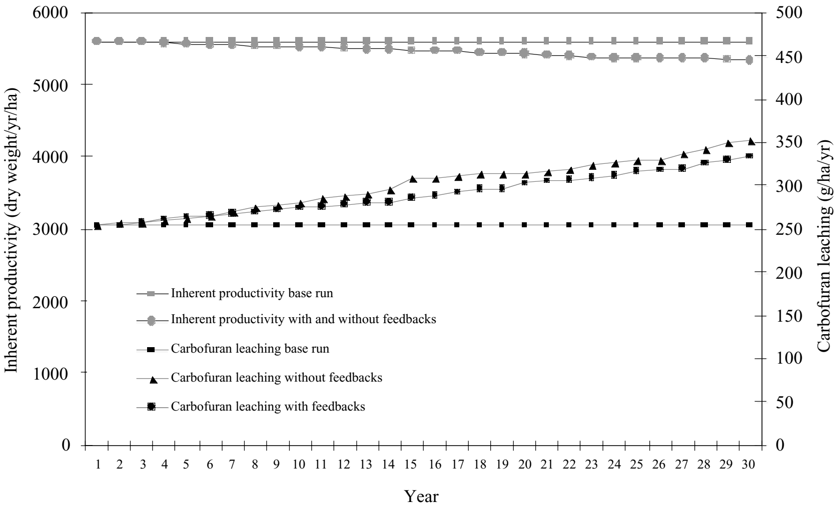

Figure 5. *The dynamics in inherent productivity and carbofuran leaching as a result of tillage erosion under different model definitions*

was implemented in the Tradeoff Analysis model by adapting the soil descriptions after each time step on the basis of the modeled rates for tillage erosion. The new soil descriptions are then the basis for new inherent productivities and the simulation of crop choices and input use. On average, inherent productivity of potatoes declined relatively little, thus producing small effects on crop choice and input choice (some substitution from potato to pasture). As a result there is no visible difference between the curves for inherent productivity with and without feedbacks (figure 5). Average carbofuran leaching decreased as a result of the reduction in carbofuran use which resulted from the decrease in inherent productivities. However, the average data in figure 5 mask the spatial variability of erosion and its impacts. Figure 6 shows that 'hot spots' emerge because of site-specific conditions favorable to tillage erosion. At sites that cross the soil-depth threshold from high to low productivity, crop choice and pesticide use are significantly impacted, as are economic returns to the system.

The threshold response of leaching is shown in figure 7 for four fields that represent the range of possible responses. In fields with low erosion rates, there is little increase in leaching. However, in fields with high erosion rates and shallow topsoil, the transition to high erosion rates occurs very quickly, from five to ten years after the erosion process (cultivation) begins. In fields with deep topsoils, the transitional period occurs between years 25 and 30.

Figure 8 shows that land use responds non-linearly to inherent productivity as well. It follows that in those sites where productivity crosses a significant threshold, land use also changes substantially. Figure 3 shows that for topsoil depth greater than 50 cm, inherent productivity is in the range of 4,000 kg of dry matter per ha. When topsoil depth declines to 25 cm, productivity falls by about 75 per cent. Figure 8 shows that farmers

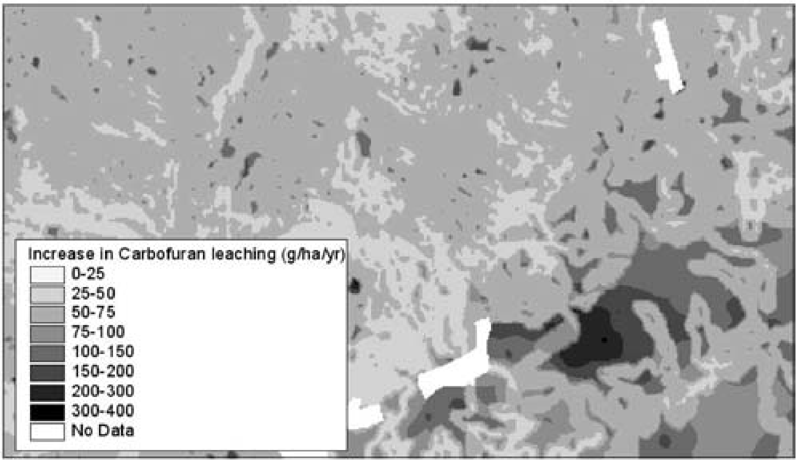

Figure 6. *The spatial variability in the increase of carbofuran leaching over a 30 year period as a result of tillage erosion and management changess*

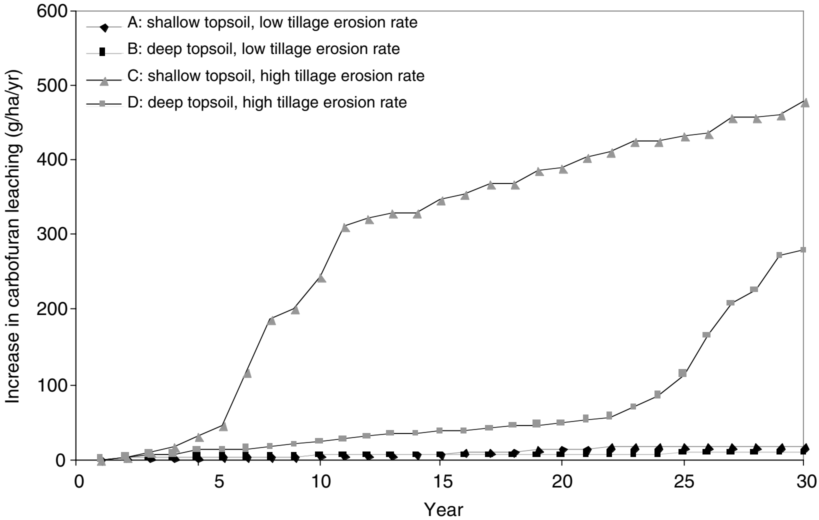

Figure 7. *The temporal dynamics in carbofuran leaching for 4 different fields as a result of tillage erosion and management changes*
Source: Stoorvogel, Antle, and Crissman (2004).

with a normal productivity level near 4,000 kg rotate potato with pasture in roughly 50–50 proportions (a fact confirmed by the survey data). However, when productivity declines to 1000 kg, the rotation shifts so that potatoes are grown only about 20 per cent of the time. Economic returns at these sites also decline by 53 per cent.

This example illustrates the important interactions between spatial properties of the system, and the interactions between management

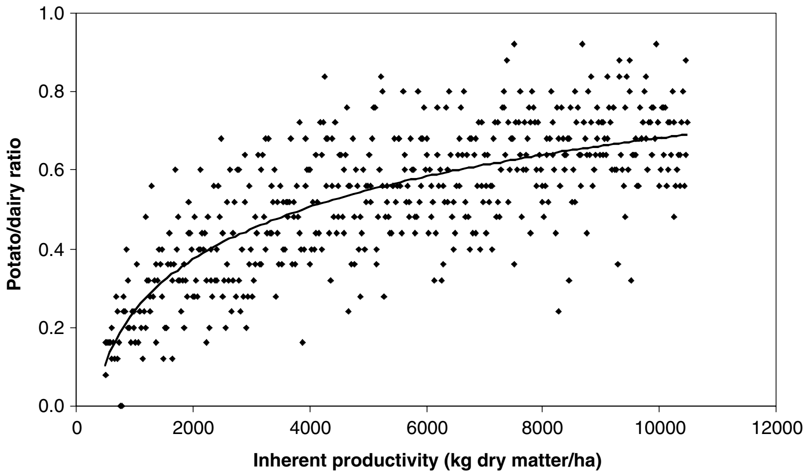

Figure 8. *Response of crop choice to inherent productivity of potatoes in the Ecuadorian potato-pasture system*

decisions (crop choice), tillage erosion, and leaching. This particular example shows that the loosely coupled model without feedbacks is a reasonably good first-order approximation. The introduction of feedbacks with productivity is important for predicting the behavior of the system where the signal being fed back is relatively strong; otherwise, the loosely coupled model without feedback provides a good approximation.

We would expect only minor differences if we introduced foresight into this model, for several reasons. First of all, the changes in inherent productivity are minor (figure 5), so these changes have only a small effect on farmers' decisions. Second, we would expect these farmers to discount future income at relatively high rates, with the result that the model without foresight should be a good approximation. However, we know that in cases where investment decisions are being made, models with foresight are relevant; for example, in the analysis of terracing investment decisions studied by Valdivia (2002).

Poverty linkages at the farm and regional levels

The spatial and temporal interactions identified in the preceding example are likely to have important implications for linkages to the welfare of farm households and the broader rural population. One could, for example, overlay the map of carbofuran leaching (figure 6) with a map of household income or poverty incidence, where one component of income is the farm income derived from crop production. Policy or technology strategies devised to mitigate environmental impacts of pesticide use would have implications for incomes and poverty. While it is beyond the scope of this paper to solve the methodological challenges that would arise in linking models of the production system to analysis of poverty and related social welfare indicators, we can identify some of the issues that need to be addressed.

At the level of the farm household, the production system will link to welfare through farm income if production decisions can be reasonably viewed as separable from other household decisions. Under the assumption of separability between production and other household decisions, the production system can be used to derive income from the household's agricultural activities, and this component can be combined with other income components such as off-farm income and asset income to jointly assess the household's poverty status and the impact that changes in the production system may have on poverty and resource degradation. In addition, linkages from poverty to farmers' behavior, and its implications for resource degradation, can be explored with these models. For example, it has been widely assumed that poor, resource-limited farmers have higher rates of risk aversion and time preference than wealthier farmers. If separability is not assumed, then the analyst is confronted with the problem of modeling both production and other household decisions as an integrated system. While the data requirements and model complexity are increased in implementing an integrated household model, the issues we have discussed in this paper regarding the design of production systems models remain relevant.

To link site-specific production models to welfare at the regional level we must address the aggregation problem. Exact aggregation is not possible with complex non-linear models, but research on statistical aggregation shows that the aggregated outcomes from these site-specific models can be defined as functions of the parameters of the underlying distributions of the models' exogenous variables (Stoker, 1982; Antle *et al.*, 1998). Noting that a model of a production system can be thought of as a model of the farm firm's supply function, it follows that it is possible to simulate the response of output to changes in output and input prices for a statistically representative sample of farms. These simulations can be used to characterize the regional supply function as well as tradeoff curves representing the corresponding changes in regional environmental indicators. For example, the tradeoff curve illustrated in figure 4 shows the combinations of tillage erosion and leaching that correspond to different output prices. The regional supply function could be combined with demand functions in partial or general equilibrium regional models to determine equilibrium prices and output, and thus provide analysts with the ability to correlate equilibrium welfare and resource indicators. In this way, it would be possible to map changes in welfare indicators such as poverty as well as economic and environmental outcomes for policy analysis. Making these linkages from spatially explicit production system models to market equilibrium models is an important topic for future research.

Conclusions

In this paper we discuss how loosely coupled and more closely coupled models of agricultural systems can be implemented using a modular modeling approach. We used the case of the Ecuador potato–pasture system to illustrate the importance of spatial heterogeneity and dynamics in production systems models. The case study showed that, whereas a system based on loose coupling of models gave a reasonable representation of the population mean, the system with closer coupling (feedbacks from biophysical processes to economic decision making) provided substantially different estimates of impacts at sites where the feedbacks were strongest, in this case at sites that were most vulnerable to soil erosion. This finding suggests, first, that dynamics and heterogeneity are important to understanding the behavior of the system, and, second, that the insights afforded by models that capture system dynamics and heterogeneity may have important implications for understanding the linkages between poverty and resource degradation.

To exploit the value of site-specific, dynamic production system models for policy and welfare analysis, a number of additional linkages need to be made at the level of the farm household and at the regional level. The agricultural system models we discussed in this paper do not include other household decision-making processes, such as the labor supply, food consumption, or healthcare decisions of the household that may be important to farm household welfare. Such generalizations are conceptually straightforward, however they may substantially increase data requirements and model complexity. Also these models may involve important behavioral parameters such as discount rates and risk aversion that may be related to wealth and other socio-economic factors. The most significant conceptual and methodological challenge is to link spatially explicit, dynamic production system models with market models so as to jointly determine equilibrium welfare and environmental outcomes.

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