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Minimum-data analysis of ecosystem service supply in semi-subsistence agricultural systems

John M. Antle, Bocar Diagana, Jetse J. Stoorvogel and Roberto O. Valdivia†

Antle and Valdivia (2006, *Australian Journal of Agricultural and Resource Economics* 50, 1–15) proposed a minimum-data (MD) approach to simulate ecosystem service supply curves that can be implemented using readily available secondary data and validated the approach in a case study of soil carbon sequestration in a monoculture wheat system. However, many applications of the MD approach are in developing countries where semi-subsistence systems with multiple production activities are being used and data availability is limited. This paper discusses how MD analysis can be applied to more complex production systems such as semi-subsistence systems with multiple production activities and presents validation analysis for studies of soil carbon sequestration in semi-subsistence farming systems in Kenya and Senegal. Results from these two studies confirm that ecosystem service supply curves based on the MD approach are close approximations to the curves derived from highly detailed data and models and are therefore sufficiently accurate and robust to be used to support policy decision making.

Key words: ecosystem services, Kenya, minimum data model, semi-subsistence agriculture, Senegal.

1. Introduction

Around the world, agricultural policies are undergoing a transformation from ones that subsidize commercial agricultural production to policies that encourage sustainable land management practices and address environmental effects of agriculture. As a result, agricultural policies increasingly are designed to provide farmers incentives to increase the supply of ecosystem services from agriculture – public goods that include wildlife habitat, visual amenities and open space, water quality protection, and greenhouse gas mitigation. A growing body of research has attempted to use site-specific data and models to implement analysis of agricultural-environment interactions and ecosystem service supply (e.g., Pautsch *et al*. 2001; Antle *et al*. 2003; Wu *et al*. 2004; Holden 2005; Lubowski *et al*. 2006; Diagana *et al*. 2007; Antle and Stoorvogel 2008). However, the kind of high-resolution biophysical and economic data used in these studies – referred to here as full-data (FD)

† John Antle (email: john.antle@oregonstate.edu) is professor, Agricultural and Resource Economics, Oregon State University, Corvallis, OR, USA. Bocar Diagana is a Policy Economist, IFDC, Ouagadougou, Burkina Faso. Jetse Stoorvogel is Associate Professor, Land Dynamics Group, Wageningen University, Wageningen, The Netherlands. Roberto Valdivia is Research Associate, Agricultural Economics and Economics, Montana State University, Bozeman, MT, USA.

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studies – are rarely available to provide timely analysis needed to support policy decision making, particularly in the developing countries. Site-specific data are often only available from special-purpose surveys, and even when they are available, often lack the geographic coverage needed for policy analysis.

In response to this situation, Antle and Valdivia (2006) proposed a minimum-data (MD) approach to analyze ecosystem service supply that can be implemented with data that are readily available in most parts of the world from existing secondary sources. The motivation for the MD approach was to provide timely, sufficiently accurate information to support policy decision making. They validated the MD approach with a case study of soil carbon sequestration in the dryland grain production system of the northern Great Plains of the United States. They found that the carbon supply curve derived from the MD approach closely approximated the carbon supply curve obtained from a FD analysis, in that case a detailed econometric-process simulation model parameterized with site-specific farm-level survey data. Their conclusion was that the MD approach could be used by analysts to provide information within the degree of accuracy needed to support policy decision making and do so using readily available secondary data at a low cost.

Since its introduction, the MD model has been made available in several formats on the world wide web (as an Excel spread sheet, and in SAS), disseminated through graduate courses and training workshops, used to evaluate ES supply for a number of production systems (e.g., Immerzeel *et al.* 2008; Nalukenge *et al.* 2009; Claessens *et al.* 2009; Stoorvogel *et al.* 2009), and is being applied in a variety of ongoing research projects in Africa, China, and Latin America. This rapid adoption of the MD approach appears to confirm the hypothesis that there is a demand for less data-intensive, less-complex models that can be implemented with existing data to support policy decision making, particularly in the context of developing countries where data availability may be limited.

The original validation analysis by Antle and Valdivia was for the large-scale, capital-intensive, monoculture wheat system typical of the Great Plains region of the United States, yet many of the applications of the MD approach are being made for small-scale agricultural systems in the developing world. Accordingly, this article has two objectives: first, to discuss how the MD approach can be adapted to represent more complex, semi-subsistence agricultural systems; and second, to provide further validation of the MD approach using case studies of soil carbon sequestration in semi-subsistence systems in Kenya and Senegal.

In the next section of this paper, we briefly review the conceptual framework developed by Antle and Valdivia (2006) to model the supply of ecosystem services. The next discusses how this conceptual model is transformed into an empirical model and addresses the issues that arise in modeling complex systems with multiple production activities. We then introduce the two case studies and review the methods used to develop detailed simulation models of the two production systems and estimate carbon supply curves. We compare the carbon supply curves from the FD and MD analyses and investigate sensitivity to key parameters. We conclude with a discussion of implications for use of the MD approach to support policy decision making.

2. Economic analysis of ecosystem service supply

Farmers' land management decisions are known to impact ecosystem function and the supply of ecosystem services valued by people, including services such as biodiversity conservation, water quality and quantity, wildlife habitat, and greenhouse gas mitigation. To increase the supply, demanders of ecosystem services must provide farmers with incentives to change their management decisions. Following Antle and Valdivia (2006), we consider a model of a farmer's choice between two production systems, a and b, in a geographic region. We consider a farmer at a site s using a production system a, which provides an expected value each period equal to $v = v(p, s, a)$, given product and input prices p. In the empirical implementation of the model discussed elsewhere, $v(p, s, a)$ is expected returns to the system. A more general objective function can be used that incorporates other behavioral factors such as risk aversion or household consumption preferences. For example, Smart (2009) shows how risk aversion can be incorporated into the MD approach, given adequate data. Also, production can be modeled as a dynamic system, and the objective function can be defined as the present discounted returns over a relevant time horizon. In the MD analysis presented elsewhere, where it is assumed that farmers must enter contracts for ecosystem service supply, we simplify the analysis by modeling the average expected returns over the relevant time horizon and annualizing any relevant fixed costs. With these assumptions, and when there is no other incentive for the adoption of b, system a is chosen if the difference in expected returns is positive, i.e., if $\omega(p, s) = v(p, s, a) - v(p, s, b) \geq 0$, and system b is chosen otherwise.

We assume that an additional quantity of ES of $e(s)$ units per hectare per time period is produced at each site s when practice b is adopted. $e(s)$ could measure soil C changes, as in the case studies presented elsewhere, or changes in other ES such as biodiversity, or could be an index of multiple ES. To derive the supply of ES in the region when there is no payment for using b, we identify each site where the difference in returns is negative, i.e. $\omega(p, s) < 0$, and add up the quantities $e(s)$ produced on those land units. For analyzing farmers' participation in contracts, however, a useful way to think about the supply of ES is to define the density function $\varphi(\omega)$ by ordering all land units according to the difference in returns, $\omega(p, s)$, for a given a value of p. Thus, in the 'base' case in which there is no additional incentive to use system b, the proportion of land units in system b is

$$r(p) = \int_{-\infty}^{0} \varphi(\omega)\,\mathrm{d}\omega, \quad 0 \leq r(p) \leq 1, \tag{1}$$

where the dependence of r on p follows from the fact that $\omega(p, s)$ is a function of p. Now define e as the average or expected quantity of ES supplied per hectare in the region. The baseline supply of ES per time period in the region with H hectares of cropland is then

$$S(p) = r(p)He. \tag{2}$$

The quantity (He) represents the maximum amount of ES that could be supplied if all sites in the region adopt system b, whereas $S(p)$ represents the quantity farmers are willing to supply absent any additional incentive.

To increase the supply of ES above the baseline quantity $S(p)$, we assume that the payment g (\$/ha) is offered to the land managers by a private or government entity for increasing the quantity of the ES. This payment can be based on the adoption of system b, or on the amount of service provided, although the payment per unit of service will generally be more efficient if the costs of quantifying the amount of service are not prohibitive (Antle *et al.* 2003). Note that the amount of ES supplied at each site is not known *ex ante* and therefore payments must be based on the expected increase in ES. The increase in ES could be estimated on a site-specific basis if sufficiently good data were available or could be based on an average rate of services estimated for the region that could subsequently be verified through a statistically based sampling and measurement scheme (e.g., Paustian *et al.* 2006; Mooney *et al.* 2004). The landowner receives a value of $v(p, s, a)$ for using practice a and $v(p, s, b) + g$ for using practice b. If the farmer is paid per unit of service, then $g = p_e e$ where p_e is the price per unit of service, and e is the expected amount of additional services produced with practice b.

The site-specific land use decisions can be linked to the regional supply of ES using the spatial distribution of opportunity cost. The area under the spatial distribution of opportunity cost on the interval $(-\infty, 0)$ equals $r(p)$ and represents those land units where farmers use system b without an incentive payment. Thus, at the point where $g = 0$, the baseline supply of ES equals $S(p)$. Those land units corresponding to the range of opportunity cost between zero and g will switch from system a to b and thus increase the supply of ES to a quantity greater than $S(p)$. Define this proportion of the land area as

$$r(p, g) = \int_0^g \varphi(\omega)\, \mathrm{d}\omega. \tag{3}$$

The supply of ES at $g > 0$ is equal to

$$S(p, g) = S(p) + r(p, g)He. \tag{4}$$

Those land units where opportunity cost is greater than g will remain in system a. As g increases, $r(p, g)$ increases and approaches $1 - r(p)$. Equation (4) shows that the total quantity of ES is equal to the baseline quantity, $S(p)$, plus the additional quantity supplied, $r(p, g)He$, because of the positive incentive. If farmers are paid only for services above and beyond the baseline quantity, the ES supply curve is defined as $S(p, g) - S(p) = r(p, g)He$.

As discussed further by Antle and Valdivia (2006), the variance of the opportunity cost of changing practices plays an important role in determining the shape of the supply curve of ES. When the variance is positive, the supply curve has a positive slope, with its concavity depending on the position of the distribution of opportunity cost in relation to the origin. As the variance decreases and approaches zero, the supply curve approaches the shape of a step function with the step occurring at the value of g where the mass of the distribution lies. This limiting case of a zero variance is equivalent to a representative farm model applied to the average land units in the region.

3. MD modeling of semi-subsistence systems

When a spatially explicit FD model is available, it can be used to simulate ES supply and, in effect, construct the spatial distribution of opportunity cost discussed in the previous section. The idea behind the MD approach to ES supply is to use available data to parameterize directly the spatial distribution of net returns for the competing activities and then use these distributions to derive the spatial distribution of opportunity cost and construct the ecosystem service supply curve. Following the original MD model presented by Antle and Valdivia (2006), we assume that the spatial distribution of opportunity cost can be approximated usefully with a normal distribution. Normality is not essential to the approach, and we test implicitly this assumption when we investigate the validation of the MD model.

In many parts of the world, secondary data are available for 'average' or 'representative' costs and returns for a geographic region such as a county, a crop reporting district, or an agro-ecozone. In the MD approach, secondary data are used to estimate mean expected net returns to each system in each region. In addition, estimates of spatial variability in expected returns are needed. Antle and Valdivia (2006) observe that if the standard deviation of yield is σ and mean yield is m, and if the per-hectare variable cost of production is $C = cY$, c a constant, then for output price P the net return above variable cost (or gross margin) is $(P-\mathrm{c})Y$, and the coefficient of variation (CV) of net returns is equal to the CV of Y which is σ/m. In semi-subsistence production systems, input cost C is typically small relative to output price, so even if cost is not proportional to yield, the CV of returns will be closely approximated by the CV of yield.

As shown in the previous section, land management decisions are determined by the spatial distribution of opportunity cost ω. The expectation of this difference is equal to the difference in the mean returns of systems a and b, and the variance of ω is given by $\sigma_{\omega}^2 = \sigma_{\mathrm{a}}^2 + \sigma_{\mathrm{b}}^2 - 2\sigma_{\mathrm{ab}}$. While secondary data often can be used to estimate the variances σ_{a}^2 and σ_{b}^2 using CVs of yield as discussed earlier, it may be more difficult to obtain data to estimate the covariance σ_{ab}, so this parameter may have to be specified *a priori* and subjected to sensitivity analysis. In many cases, the covariance σ_{ab} is likely to be large relative to the variances – e.g., the returns to a crop grown with improved soil fertility management practices should have a relatively high and positive – but not perfect – correlation with the returns to the crop grown with conventional practices. Note that if $\sigma_{\mathrm{a}}^2 \approx \sigma_{\mathrm{b}}^2 = \sigma^2$, then substituting σ^2 into the expression for σ_ω^2 it follows that $\sigma_\omega^2 \approx 2\sigma^2(1 - \rho_{\mathrm{ab}})$ where ρ_{ab} is the correlation between returns for systems a and b. Henceforth, ρ_{ab} is referred to as the *between-system correlation*. Under this approximation, as ρ_{ab} approaches 1, σ_ω^2 approaches zero, and the supply curve approaches a step function with the step occurring where the opportunity cost equals the ecosystem service price. As ρ_{ab} approaches zero, σ_ω^2 approaches $2\sigma^2$ and the supply curve takes on a positive slope.

Generalizing to a case in which there are multiple activities in each system requires determining how the complete system is composed of the individual activities and then deriving the means and variances of each system. In a FD model, the allocation of land to each activity is usually determined endogenously. With the information available in MD analysis, endogenous determination of land allocation is not feasible, so we specify as model parameters the average or representative share of land, w_{zi}, allocated to a productive activity i (e.g., a crop or livestock production activity) in system z. This information is typically available for the base system a and is also available for system b if it is already in use. When the alternative system b is one that has not yet been implemented, then the likely land allocation within the system may be uncertain, and the analyst may need to evaluate the effects of different land allocation assumptions with sensitivity analysis.

Using this approach, for the ith activity in system z, the expected returns are $v_i(p, s, z)$, so the expected return for the system is $v(p,s,z) = \sum_{i=1}^{n} w_{zi} v_i(p,s,z)$. Accordingly, letting the variance of returns to activity i in system z be ϕ_{zi}^2 and the covariance between activities i and j be ϕ_{zij}, the variance in returns for system z is

$$\sigma_z^2 = \sum_{i=1}^{n} w_{zi}^2 \phi_{zi}^2 + 2 \sum \sum_{i \neq j}^{n} w_{zi} w_{zj} \phi_{zij}. \tag{5}$$

As noted earlier, estimates of variances in returns are often available and may be approximated by the variance in yields. In some cases, data may be available to estimate covariances in returns or yields, but in many cases obtaining estimates of covariances may be problematic. Often, it is reasonable to assume that there is a moderate, positive correlation between returns to the activities in a farming system, particularly when farmers are growing multiple crops to diversify risk. Given the difficulty in estimating distinct values for all of the covariances, the MD models presented below use the assumption that the correlation coefficients between returns to activities within each system are equal. Letting this *within-system correlation* be φ_z we then have $\phi_{zij} = \varphi_z \phi_{zi} \varphi_{zj}$ for all $i \neq j$. Below we explore the sensitivity of carbon supply curves to the value of φ_z.

Once the system means and variances of returns are calculated, the mean and variance of the opportunity cost of changing practices can be calculated as discussed earlier, and then using equations (3) and (4) the contract participation rate and the supply curve can be simulated. This can be accomplished efficiently under the assumption of normally distributed returns by using the fact that the difference of two normally distributed random variables is itself normal, and calculating the area under the cumulative normal distribution up to the level of the payment. Alternatively, in cases where either normal or non-normal distributions are used, the simulation may be implemented by repeatedly sampling from the distributions of net returns for each activity and selecting the activity with the highest expected returns. This process is carried out once for the baseline case (no payments for ecosystem services) and then for each payment level that is of interest. In the baseline case, we would expect the land allocation to approximate the observed land allocation (the point $S(p)$ in Figure 1).

Software for data entry and simulation of the MD model is available to be downloaded from the world wide web. The data are organized in sheets in an Excel file, which provides a convenient template for data collection and for implementing the simulations. Simulation model versions are available programmed in both Excel and the Statistical Analysis System.

4. MD model validation for carbon sequestration in Kenya and Senegal

In this section, we investigate whether the MD model based on population means and variances can reasonably approximate the carbon supply curves derived from more detailed models estimated with site-specific farm-level data (FD model). We first describe the case studies and the general structure of the

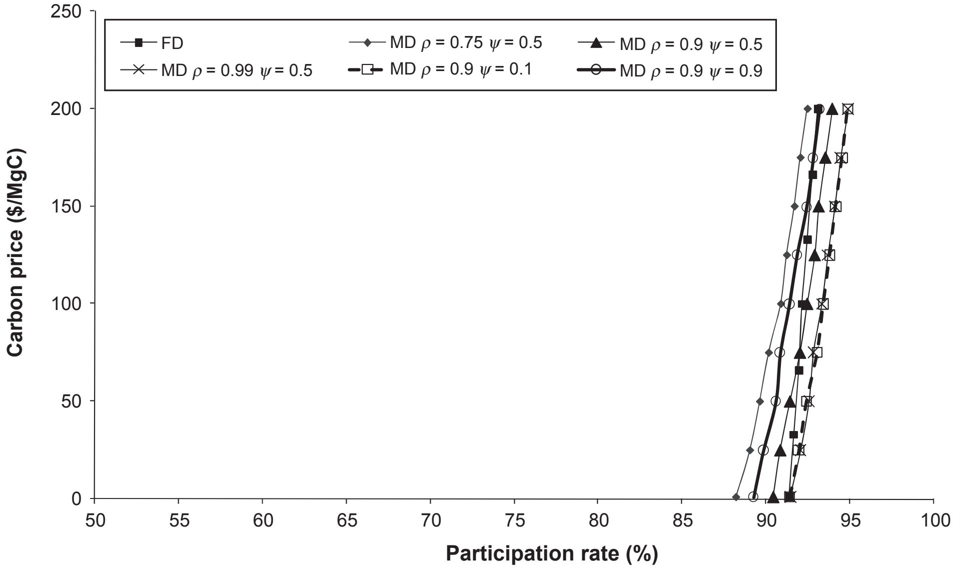

Figure 1 Carbon contract participation rates for Machakos, Kenya, for full-data and MD models with alternative values for correlation between systems (ρ) and correlation between activities within systems (ψ).

FD simulation models for Kenya and Senegal and then present the validation results.

4.1 Kenya case study

The Kenya study area includes Machakos and Makueni districts southeast of Nairobi. The two districts cover approximately 14 000 km^2 and range in altitude between 400 and 2100 m above sea level. The semi-arid climate in the study area has low, highly variable rainfall, distributed in two rainy seasons. The annual rainfall average ranges from 500 to 1300 mm, and mean annual temperature varies from 15 to 25°C. Soils in the region are strongly weathered and generally deficient in nitrogen and phosphorus with a low (< 1%) organic matter content. Moreover, low infiltration rates and susceptibility to sealing makes them prone to erosion, especially since most of the rains occur at the beginning of the growing season when the land is still bare. The farms can be characterized as subsistence-oriented mixed farming systems that include both crop and livestock production. Maize is the most important staple crop that is sold for cash, and a wide variety of subsistence crops are grown, such as vegetables, fruits, and tubers. Many farms apply manure to crops, but use of mineral fertilizer is limited. The models were estimated using farm survey data for 120 households in six villages were obtained from studies conducted in the 1997–2001 period (de Jager *et al.* 2001; Gachimbi *et al.* 2005).

4.2 Senegal case study

The Nioro area of Senegal contains about 103 000 hectares of cropped area, or about 5% of Senegal's agricultural area, and lies in the sudano-sahelian zone of the Peanut Basin. The rainy season lasts from June to October, and the total annual rainfall is about 750 mm. Annual temperatures average 27.5°C, and the mean maximum and minimum temperatures are, respectively, 38 and 15°C. The cross-sectional data used in this study come from farm surveys conducted by the Ecole Nationale d'Economie Appliquée in 2001 and surveys managed by the Senegal Agricultural Research Institute in 2003 and 2004 (Diagana *et al.* 2007). More than a hundred households in thirteen villages in the Nioro area were surveyed to collect detailed socioeconomic and agricultural production data including household demographic characteristics, labor availability, annual food grain production and consumption, annual income and expenses, and agricultural inputs and outputs. The crop system is principally millet and peanut grown in annual rotation. Average peanut and millet crop yields from the sampled fields are low, and parcels are small, and mineral fertilizer use is low. Few farmers use organic fertilizers, presumably because of the limited availability of manure and costs of collecting and storing manure with existing livestock management practices. Incorporation of crop residues also is practiced on a limited basis, primarily because of the value of crop residues as livestock feed.

4.3 FD simulation model design and implementation

The FD simulation models for the Kenya and Senegal case studies are described in Antle and Stoorvogel (2008), and Diagana *et al*. (2007) provide further details for the Senegal study. The models were implemented using the Tradeoff Analysis (TOA) software, which provides a modular approach to agricultural system modeling (Stoorvogel *et al*. 2004). The TOA software integrates the following components:

4.3.1 Data

The analysis utilizes three types of data: environmental, experimental, and farm survey. The environmental data describe the spatial variation in soils and climate and are organized in a GIS format and are used with experimental data to parameterize models. The survey data describe the farms and the land management decisions of farmers and are used to parameterize the economic models.

4.3.2 Crop and carbon models

The DSSAT cropping system model (Tsuji *et al*. 1994; Jones *et al*. 2003) is used to estimate the spatial and temporal variation in indexes of inherent productivity of the land (crop yield estimated with standard management) that is driven by soil and climate variations. In the Kenya study, the carbon model of Stoorvogel (2007) was used to estimate changes in soil C associated with changes in management practices. In the Senegal case, the DSSAT/Century model (Gijsman *et al*. 2002) was used to estimate inherent productivities and soil C values for the economic analysis.

4.3.3 Econometric-process simulation models

Using farm survey data, econometric production models are estimated and then simulated using the inherent productivities from the crop models. The economic simulations provide site-specific land use and management decisions for the base system and for the practices specified under the carbon contract. These decisions can then be used to estimate impacts of carbon contracts on poverty and sustainability.

4.3.4 Environmental process models

As appropriate to the analysis, the management decisions from the economic simulation model (e.g., land use, fertilizer use, pesticide applications) can be used as inputs into environmental process models to estimate impacts on soil organic matter and nutrients, soil erosion, pesticide fate, water quality, and other processes of interest.

4.4 Characterization of carbon contracts

The goal of the FD analyses was to simulate the participation of farmers in soil carbon contracts that provide economic incentives for adoption of carbon-sequestering practices. In the baseline conditions that are observed without carbon contracts, the data from Kenya show that the majority of farms without irrigation are using little or no fertilizer with their cash crop (maize), and those that do use purchased mineral fertilizer apply only about 80 kg/ha of active ingredient to maize and almost none to other crops. Farmers do apply some manure and other organic amendments, but also at very low rates, averaging about 350 kg/ha across the typical farm. In the simulated carbon contracts for Kenya, the FD analysis assumes that farmers must apply at least 60 kg N/ha per season and at least 600 kg of organic fertilizer per ha per season.

In the Senegal data, a large proportion of farms (81%) use some fertilizer for their cash crop (peanuts), although at a low average rate of less than 60 kg/ha of active ingredient, and in the other main crop, millet, only about 35% of the fields receive mineral fertilizer at an average rate of about 40 kg/ha. Peanut crop residues are marketed as animal feed, and most other crop residues are fed to animals, burned, or used for other purposes. Consequently, there is a substantial loss of organic matter from the system, and little organic matter is re-incorporated into the soil. In the Senegal FD analysis, a number of different scenarios were considered, but the analysis showed that two scenarios were of particular interest. Both of the scenarios required farmers to utilize at least 60 kg/ha of mineral fertilizer on peanuts and at least 40 kg/ha on millet. The two scenarios differed in terms of their requirements for peanut crop residue incorporation, with one scenario requiring 50% of crop residues to be incorporated into the soil and the other requiring 100%.

The two case studies each assume that to increase the stock of soil organic carbon on a land unit, a farmer must make a change from a base production system that had been followed over some previous period (the historical land use baseline) to the alternative system with increased use of organic and mineral fertilizers. The carbon rate used in the contracts is estimated by agro-ecological zone using field measurements and models. The two studies considered carbon prices ranging from zero to $200 per metric ton C, a range considered relevant in studies of a prospective global carbon trading system (Paustian *et al.* 2006).

4.5 Construction of MD data

The FD models described earlier are based on farm surveys that were designed to represent farm populations. The goal of the MD validation is to investigate the ability of the MD models to approximate the FD models. To implement the MD analysis, the data used to estimate the FD econometric models were used to estimate the population parameters (mean yields, yield CVs, mean costs of production) for the crops in the base systems, for those farmers who used low levels of mineral fertilizer and manure. For the system under a carbon contract, levels of inputs required under the contract were used to estimate the mean yields and cost of production. As a starting point in the analysis, the same CVs were used for the base system and for the system with the carbon contract, implying that if the mean returns increase under the carbon contract, the variance of returns would also increase relative to the base system. However, there is evidence suggesting that with higher levels of inputs the yield variability may change, and so we consider below the sensitivity of the MD models to alternative assumptions about CVs. Also note that in a MD analysis, various methods could be used to estimate the technical potential of the system (i.e., the carbon rates), ranging from highly complex models such as Century to simpler models or estimates based on previous research. Here, our goal is to investigate the reliability of the MD economic model, so we use the carbon rate estimates from the FD analysis.

4.6 Comparison of FD and MD model results

To facilitate comparison across models and scenarios, we present results using the contract participation rate defined in equation (3). Figure 1 presents the FD carbon contract participation curve from the Kenya study, and the MD curves for several combinations of the correlation of expected returns between system (defined above as ρ_{ab}) and the correlation between activities within systems (defined above as φ_z). To interpret the results, note that the carbon contract makes fertilizer available to farmers that would not be using it otherwise and that only about 20% of farmers in Machakos use mineral fertilizer in maize production. Moreover, the FD model shows that fertilizer is profitable for most farmers, implying that fertilizer availability is constraining fertilizer use (as confirmed by other studies such as Jayne *et al.* 2003 and Salasya 2005). Consequently, the FD curve shows a high participation rate with a zero carbon payment, because of the fact that the model makes fertilizer available to farmers as part of the carbon contract. The other feature of the curve is its inelasticity with respect to the carbon price, reflecting the fact that most farmers are willing to participate to obtain access to fertilizer. The MD models produce a somewhat more elastic participation curve than the FD model, but the MD model nevertheless provides a participation curve that is a very close approximation to the FD model's curve. Figure 1 also shows that the MD curve is not very sensitive to the between-system (ρ) or the within-system (ψ) correlations.

Figure 2 presents results from the Senegal study for the FD and MD models, for the two scenarios considered (50 and 100% crop residue incorporation), with the between-system correlation equal to 0.8 and the within-system correlation equal to 0.5. In Kenya, very few farmers use more than the contract amount of fertilizer and manure, whereas in the Senegal case many more farmers use positive amounts of fertilizer. The FD Senegal model scales carbon credits in proportion to how much fertilizer a farmer uses in relation to the amount required by the contract. As a result, the technical potential of the FD model occurs at an adoption rate of about 80% (Figure 2). Although there is no comparable way to represent such a complex contract

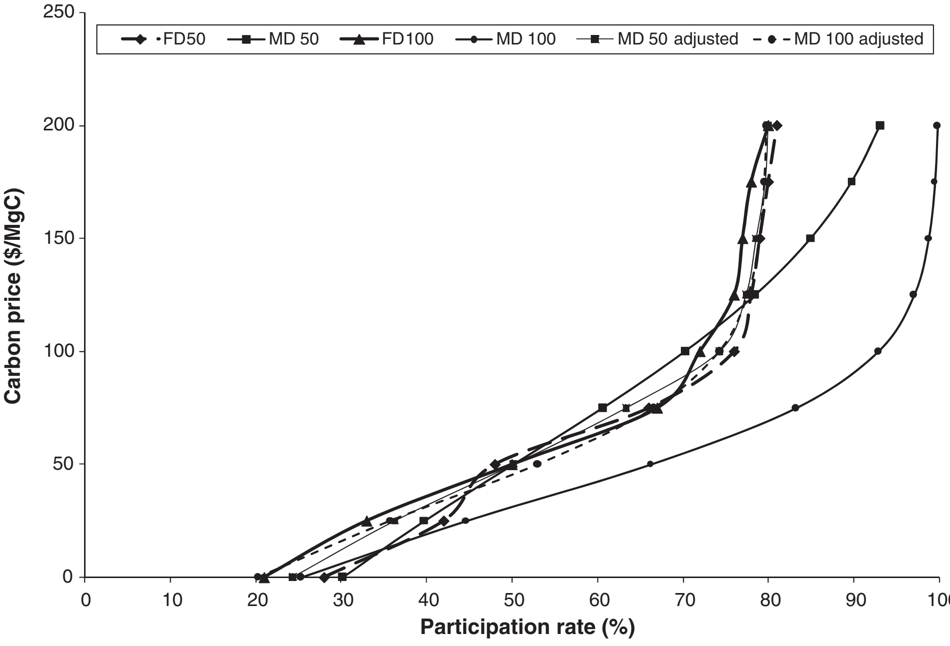

Figure 2 Contract participation rates in Nioro, Senegal for MD and full-data models, for 50 and 100% crop residue incorporation (between-system correlation $\rho = 0.8$ and within-system correlation $\psi = 0.5$).

participation mechanism in the MD model, it is possible to scale the adoption probability so that the maximum adoption rate is 80% rather than 100% at a high carbon price. Figure 2 shows that without this adjustment, the MD model does indeed overpredict adoption, particularly at higher carbon prices, whereas the adjusted adoption curves are a very close approximation to the FD model's adoption curves. This adjustment substantially improves the 100% residue incorporation scenario, whereas in the case of the 50% scenario the adjustment is too large at lower prices and moves the intercept below the FD model's intercept.

Another interesting feature of the Senegal FD curves is their somewhat irregular shape, explained by the fact that farms in different villages are willing to enter contracts participation at different prices. The MD model tends to produce smoother curves because of the use of the normal distribution within each village. We can conclude that with the adjustment for the constraint on technical potential, the MD model provides a prediction of contract participation very similar to the FD model, although without this adjustment the MD model overpredicts adoption in the 100% residue incorporation scenario.

Figure 3 shows that the Senegal MD model is somewhat sensitive to different values of the between-system correlation ρ, holding the within-system correlation at 0.5. A very high value of ρ increases the tendency of the model to approach a step function and thus overestimate adoption rates in the

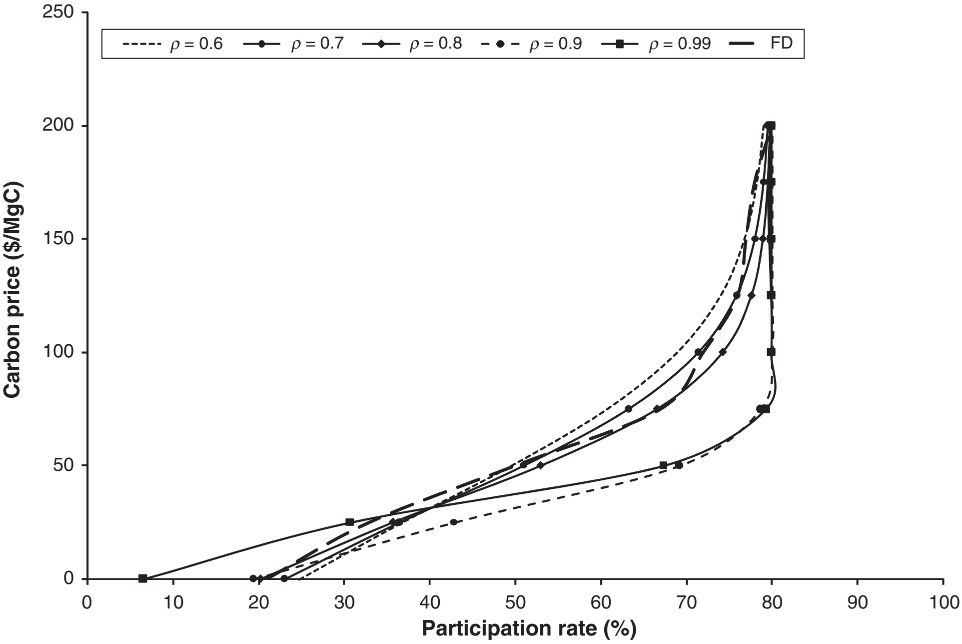

Figure 3 Sensitivity of carbon contract participation rates to between-system correlation (ρ) for 100% crop residue scenario, Senegal.

mid-range of the carbon price. Similarly, Figure 1 shows that in the Kenya case the model is not very sensitive to the within-system correlation. Analysis of sensitivity to the within-system correlation coefficient (ψ) showed that neither model was sensitive to this parameter, so it was set at the mid-range value of 0.5 for all the results presented here.

Figures 4 and 5 provide a sensitivity analysis to the coefficients of variation in yield used to represent spatial variability in returns in the MD models. Changes in the CV will shift the participation curve differently depending on the mean of the opportunity cost distribution in relation to zero opportunity cost. In the Senegal case (Figure 4), the mean of the opportunity cost distribution is positive, therefore a reduction in the CV shifts more of the mass of the distribution above zero and therefore shifts the intercept of the participation curve leftward; an increase in the CV has the opposite effect. However, as the carbon price increases above the mean opportunity cost (about $30/MgC in this case), the curves cross over so that the changes in CV have the opposite effect. In the Kenya case (Figure 5), the CV of yield is inversely related to the position of the participation curve because the mean of the opportunity cost distribution is negative. Thus, as the variance decreases, more of the mass of the distribution is below zero, and the opposite is true as the variance increases. While Figures 4 and 5 show that changes in the CV do affect participation rates as theory predicts, the fact that the CVs are being varied by 50% and participation rates are changing by relatively small

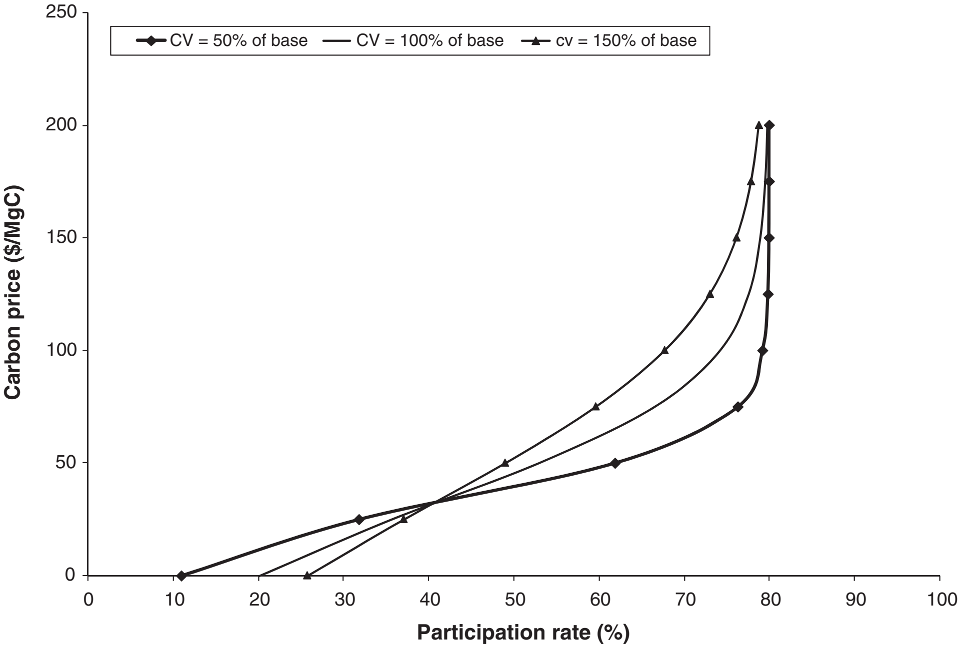

Figure 4 Sensitivity of carbon contract participation rates to yield coefficient of variation under 100% residue incorporation scenario, Senegal.

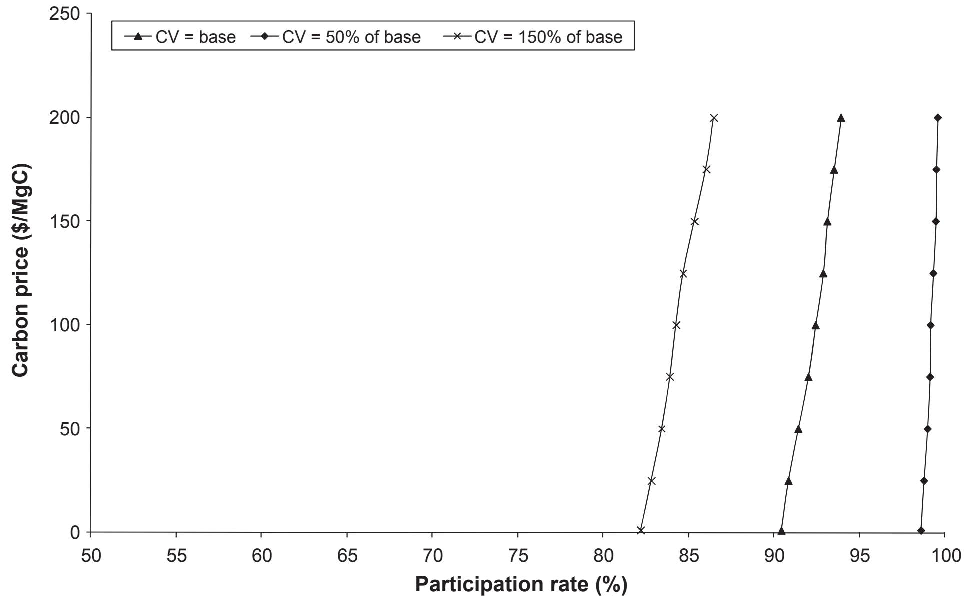

Figure 5 Sensitivity of carbon contract participation rates to yield coefficient of variation, Kenya.

amounts suggests that the supply curves will not be substantially impacted by relatively small errors in estimates of CVs. One implication of this finding is that the use of the CV of yield to approximate the variability in net returns, as discussed earlier and as implemented in the MD model, is sufficiently accurate to provide reliable estimates of ecosystem service supply curves.

Antle and Valdivia (2006) argued that using a minimum-data approximation for policy analysis is justified because policy analysis demands 'sufficiently accurate' analysis. They argued that an analysis that is accurate within an order of magnitude is sufficiently accurate. In the results presented here, the prediction errors of the MD models averaged over the range of the simulations are all less than 5% of the FD model predictions. Considering the various errors possible in this type of analysis, and the demands of policy analysis, we conclude that the MD models are sufficiently accurate for policy analysis. As noted earlier, the MD model presented here is based on a normal distribution of opportunity cost. The reliable performance of the MD models therefore can be considered a validation of the normality assumption. Finally, it should be kept in mind that the model presented here assumes decision makers are risk neutral and choose between systems based on expected returns. Smart (2009) shows how risk aversion can be incorporated into the MD model, and using the Kenya case study presented here, finds that if decision makers are highly risk averse, their willingness to participate in carbon contracts could be substantially reduced below the rate predicted by the risk-neutral model because increased fertilizer use is associated with an increase in maize yield variability. These results suggest that analysts should consider carefully other factors such as production risk and risk aversion that could affect farmers' willingness to participate in ecosystem service contracts. However, it should be emphasized that the potential importance of other factors such as risk does not negate the validation of the MD approach presented here, because the original models of the Kenya and Senegal systems also were based on the assumption of risk neutrality.

5. Conclusions

This paper discusses the use of the minimum-data (MD) approach to analysis of ecosystem service supply for analysis of semi-subsistence agricultural systems and validates the approach with two case studies. The MD approach is proposed as a particularly appropriate approach for policy analysis in situations, such as semi-subsistence agriculture, where data availability is limited. However, the complexity of semi-subsistence systems raises the question whether the minimum-data approach can provide sufficiently accurate predictions to support informed decision making. The approach taken in this article is to assess whether MD models can reasonably reproduce results from complex systems models based on site-specific data.

The two case studies represent different degrees of spatial and system complexity in small-scale, semi-subsistence agriculture and thus differ substantially from the large-scale, capital-intensive wheat system used in the original validation exercise by Antle and Valdivia (2006). The results of the analysis show that the MD contract participation curves for soil carbon sequestration are good approximations to the curves estimated using FD models. Moreover, the simulated contract participation curves are robust to key parameters needed to estimate the degree of spatial variability in opportunity cost, notably the between-system and within-system correlations between expected returns, and the estimated coefficients of variation in crop yields. The Senegal case study presented an interesting example of a more complex contract design, which limited the overall participation rate in carbon contracts, and a simple adjustment of the model was able to adequately take that aspect of the analysis into account. We conclude that these two case studies provide further evidence to support the use of the MD approach in analysis of ecosystem service supply in general, and more specifically in production systems with multiple activities such as those typical of semi-subsistence agriculture in developing countries.

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