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The evolution of agricultural soil quality:

A methodology for measurement and some land market implications

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Abstract

The limited observability of soil quality has both static and dynamic dimensions, and together, these may contribute to a form of land market failure in which underinvestment in soil conservation occurs. In this paper, we apply two innovative econometric approaches to crop trials data from a Univ. of Wisconsin research station to examine the effects of rotations and fertilizer use on the dynamics of soil quality and corn yields. In the first approach, we develop a reduced-form, random coefficients model of yield responses to nitrogen fertilizer and rotations, in which both short- and long-run substitutability of N fertilizer for rotation can be evaluated. The second approach exploits the recursive properties of a dynamic structural model to explicitly recover an indirect but general measure of soil quality. This measure, based on readily available data, can contribute to the improvement of land market performance by reducing informational asymmetry. At a methodological level, our analysis also highlights the complementarity of the two econometric approaches used.

Introduction

Environmental economists and policy makers often worry that farmers underinvest in soil conservation. One prominent contribution to the analytical literature on this subject identifies the truncation of planning horizons and/or subjective discount rates in excess of social rates of time preference as important factors, since these cause farmers to undervalue returns to soil-conserving investments (McConnell). While the argument on subjective discount rates is unambiguous, that on the truncation of planning horizons—for example, by sale of the land—is only supported when land prices (i.e., salvage values) do not reflect true soil quality (Clarke). In the extreme, if soil quality played no role in the determination of land prices then a farmer would rationally exhaust the soil before offering the farm for sale. More generally, if soil quality cannot be accurately observed then this may prevent the complete capitalization of soil-conserving investments into land prices (Gardner and Barrows; Blaine *et al.*). The limited observability of soil quality has both static and dynamic dimensions, and together, these may contribute to a form of land market failure in which underinvestment occurs.

Although no party to a potential land transaction may have perfect information, the capacity of the seller to accurately assess soil quality is greater than that of a potential buyer. Asymmetric information about the properties of goods may prevent the efficient operation of markets—the central insight of Akerlof's famous "market for lemons". However, agricultural land markets differ from the markets for many other goods in that the *current* state of the land is only part of the necessary information set. If land is degraded, for example by intensive cultivation over a period of years, then potential buyers need to know not only the extent of the degradation, but also the possible recovery paths and the costs of potential management regimes along the path. Whether fertilizer or other inputs can serve as substitutes for soil quality is part of the puzzle (Burt; Walker and Young; Taylor *et al.*), but in that case too the answer depends on the underlying dynamics of soil quality depletion and recovery.

Conventional soil quality measures fall short of solving the unobservability problem, because they capture only a limited range of current soil characteristics and provide little direct information about the path dynamics of soil quality. Indeed, designing a reliable and general measure of soil quality has been a fundamental constraint to even a wider range of scientific and policy concerns (Karlen *et al.*). Soil scientists and other researchers working on soil quality indices that combine key physical, chemical, and biological properties of soil face serious conceptual challenges, especially deciding on which of these properties to include and how to integrate them, in ways that ensure that the resulting indices are accurate and comparable across heterogeneous soils (Granatstein and Bezdicek; Rodale Institute). Moreover, time series measures of soil properties and of their sensitivity to various management practices are scarce and expensive to generate. For these reasons many soil quality studies select one or a few properties, often aggregated into a single index with unknown or subjective weights, as proxies for a more general measure (for example, Smith *et al.* (1993) and Rhoton and Lindbo).

Agricultural economists studying soil quality outcomes and optimal rotation, tillage, or fertilizer practices have also tended to use one or two soil attributes to proxy for quality (Burt; Walker; van Kooten *et al.*). Moreover, data and methodological constraints restricted empirical analyses of the dynamics of soil quality evolution. In van Kooten *et al.*, the farm plot data from which information on rotational choices, soil quality (measured by soil depth and moisture), and yields are drawn only span four years, although they do have variations in fertilizer application. Their study is thus unable to reach robust conclusions on the long-term effects of rotational choices or the substitutability of fertilizer for soil quality in the long run. Burt's study, by contrast, builds on a longer time-series on rotational choices and wheat yield outcomes. Soil quality is measured by two proxies: topsoil depth and organic matter content. However, it lacks information on variation in fertilizer use, so that the short- and long-run role of fertilizer as a substitute for soil quality cannot be explicitly evaluated.

In this paper, we develop a method based on readily observable outcomes (in this case, corn yields) that can explain current soil quality in terms of past management regimes and predict its evolution under future regimes - exactly the type of information we have argued may be necessary for more efficient operation of agricultural land markets. Specifically, we apply two innovative econometric approaches to crop trials data from a University of Wisconsin research station to examine the effects of rotations and fertilizer use on the dynamics of soil quality and corn yields. In the first, we estimate a random coefficients model of yield responses to nitrogen fertilizer and rotations. The results permit an evaluation of the substitutability of N fertilizer for rotation in maintaining yields over the short and long run. However, we refer to the approach as "reduced-form" because it does not recover an explicit measure of soil quality. In the second, we break new ground by exploiting the recursive properties of a dynamic structural model to recover an indirect but general measure of soil quality. This approach enables an explicit analysis of the relationship between soil quality and the control variables (rotation and fertilizer), as well as attention to the soil quality-productivity nexus.

Both models give statistically significant estimates of key parameters with appropriate signs, and the results across the two models are strongly consistent. They reveal new information both about the soil quality effects of intensive cultivation and about soil quality recovery paths. The main empirical findings are first, that while N fertilizer is in the short run an effective substitute for soil quality, in the long run continuous corn cropping causes declines in soil quality that cannot be alleviated by higher N application rates. Second, rotations with nitrogen-fixing crops do provide a means for sustaining or recovering soil quality and yields. As a guide to the dynamics of soil quality recovery, we use the estimates from the two models to evaluate the speed at which soil quality returns to base levels under alfalfa following long periods of intensive cultivation.

The models and the results make empirical and methodological contributions to our understanding of the dynamics of soil quality. If unobserved information on soil quality impedes efficient land market performance, we offer a measure that uses readily available data to capture both the static and the dynamic aspects of the problem. At a methodological level, our analysis highlights the complementarity of the two econometric approaches used, and in particular draws attention to the tradeoff between the rigid functional form needed to make the dynamic model tractable and the value of deriving a general, structural estimate of soil quality. In a concluding section we discuss the value of further research on the dynamics of soil quality, particularly in relation to land market issues.

The Lancaster Legume-Cereal Crop Trials

We use data from a long-term study of yields of economically important crops under a legume-cereal rotation at the University of Wisconsin's Lancaster Research Station. Since this experiment began in 1967, seven different crop rotations have been applied on 21 crop sequence plots with replicate plots. The rotations have ranged in intensity from continuous corn (CCCCC) to corn-soybeans-corn-oats-alfalfa (CSCOM) to continuous alfalfa (MMMMM), and the usable data set spans from 1972 to 1995 (for further details of the data see Kim *et al.* and Vanotti and Bundy).

Nitrogen fertilizer is applied only to corn plots and at four distinct levels on sub-plots (most recently, 0, 50, 100, and 200 pounds per acre). Thus, two features of the experimental design at Lancaster shape the subsequent econometric specifications. First, the only variations in management practices are in rotation and N fertilizer use (although new seed varieties are tried in different years), so our study focuses only on how these practices affect the dynamics of soil quality and corn yields. Second, because N is applied only to corn, measures of rotation and N use are strongly collinear. To resolve this collinearity problem, we combine rotation choices and N levels into a single index to measure their contributions to the uptake and carryover of N in the soil.

Constructing this rotation-fertilizer index is made relatively easy by estimates of N uptake and carryover generated by Vanotti and Bundy (1994, 1995) and by Vanotti, Leclerc, and Bundy using the crop trials data. In the case of legumes, nitrogen uptake is measured as negative (these are N-fixing crops), and in the case of N carryover from previous fertilizer applications, that value is also subtracted from the index (for details see Kim *et al.*). By construction, if no crops were planted on a given plot the rotation-fertilizer index for that plot and year would be zero. Figure 1 shows the average amount of N uptake after taking account of both the uptake effects of rotations and the carryover effects from previous fertilizer applications. We use these cardinal estimates to construct, in effect, an ordinal ranking of rotation and fertilizer applications with its highest value in a rotation of corn and no fertilizer, its lowest value in rotation with alfalfa. The measure thus reflects a strictly negative relation between N application levels and the amount of N uptake by corn.

A Random Coefficients Model of Yields, Rotations, and Fertilizer Use

We first examine the short- and long-term effects of crop rotations and N use on corn yields using a random coefficients model (RCM) (Swamy; Hsiao). This approach is explicitly designed for situations where the parameters of the estimated relationship may vary over time or space. Previous applications to agricultural production problems have used RCM approach to obtain improved estimators in the presence of unobserved sources of variation such as rainfall or pests (e.g., Smith and Umali). However, the RCM is a powerful and parsimonious technique to control for *known* fixed effects like past crop rotations that might have plot-specific impacts.

The RCM specification for corn yield response is given in equations (1) and (2):

$$\mathbf{y}_i = \beta_{0i}\mathbf{N}_i + \mathbf{X}_i\beta_1 + \varepsilon_i, \quad i = 1, \ldots, n, \tag{1}$$

$$\beta_{0i} = \mathbf{Z}_i\gamma + \eta_i, \tag{2}$$

where $\mathbf{y}_i$ is a vector of time-series observations on corn yields for plot i, $\mathbf{N}_i$ is a vector of time series observations on the level of N fertilizer application for plot i, $\mathbf{X}_i$ denotes a matrix of time series observations of exogenous variables. $\boldsymbol{\beta}_1$ is a vector of parameters, and ε_i is a vector of uncorrelated random variables with zero mean and variance-covariance matrix $E\varepsilon_i\varepsilon_j^{'} = \sigma_{ij}^2 \mathbf{I}_T$. β_{0i} is a random coefficient that varies according to (2). $\mathbf{Z}_i$ and γ are vectors of known and unknown constants, respectively. η_i is an unobservable random variable with zero mean and variance-covariance matrix $E\eta_i\eta_i^{'} = \lambda_i$ and $E\eta_i\eta_j^{'} = 0$. It is also assumed that ε_i and η_i are uncorrelated with each other. In this specification plot-specific variability in the marginal effect of N fertilizer on yield, i.e., the heterogeneous yield response resulting from soil quality differences, is measured by the random coefficient, β_{0i}. The key variables that need to be further specified are in $\mathbf{X}_i$ and $\mathbf{Z}_i$. Both involve measures of crop rotation, so explaining them helps to illustrate how rotation and N use are specified in the econometric analysis.

The matrix $\mathbf{X}_i$ includes variables representing the short-term and long-term effects of alternative crop rotations. We develop three rotation indexes for each year t and each plot i, based on the N uptake information discussed above. RI1, the current value of the rotation index, equals the N uptake of the current period's crop plus the N fertilizer carryover. RI5, a five year moving summation of RI1, provides a measure of the short-term rotation flow. CRI, the cumulative summation of RI1, is constructed to capture the long-term rotation effect. The vector $\mathbf{X}_i$ contains a constant term plus RI1, RI5, and CRI, the mean deviation over T years for July Growing Degree Days (GDDDEV), the mean deviation over T years for July precipitation (PRECDEV), dummy variables for different corn varieties (D1-D10, D12) used in the experiments, and a dummy variable (Dummy1988) for the year 1988, which was extremely dry.

$\mathbf{Z}_i$, the matrix representing the plot-specific characteristics, consists of a constant, $ZRI1_i$, the mean value in time t over all previous time periods of the current rotation index (RI1), and $ZRI5_i$, the mean value in time t over all previous time periods of the five year rotation index (RI5). $\mathbf{Z}_i$ thus characterizes plot-specific characteristics in terms of initial differentials or those that might arise as a function of past crop choices.

Combining equations (1) and (2), the full specification is given by:

$$\mathbf{y}_i = \mathbf{W}_i\gamma + \beta_1\mathbf{X}_i + \mathbf{u}_i\,, \tag{3}$$

where $\mathbf{W}_i = \mathbf{N}_i\,\mathbf{Z}_i$, $\mathbf{u}_i = \mathbf{N}_i\,\eta_i + \varepsilon_i$ and $E\mathbf{u}_i\mathbf{u}_i' = \mathbf{\Omega}_i = \mathbf{N}_i\lambda_i\mathbf{N}_i' + \sigma_i^2\,\mathbf{I}_T$. The BLUE of $\boldsymbol{\beta}_1$ and γ in (3) is the GLS estimator,

$$\begin{bmatrix} \hat{\beta}_1 \\ \hat{\gamma} \end{bmatrix}_{GLS} = \left[\sum_{i=1}^{N}\begin{bmatrix} X_i' \\ Z_i'N_i' \end{bmatrix}\Omega_i^{-1}(X_i, N_iZ_i)\right]^{-1}\left[\sum_{i=1}^{N}\begin{bmatrix} X_i' \\ Z_i'N_i' \end{bmatrix}\Omega_i^{-1}y_i\right]. \tag{4}$$

Amemiya (1978) proposed a simplifying method to obtain $\begin{bmatrix} \hat{\beta}_1 \\ \hat{\gamma} \end{bmatrix}_{GLS}$. Let

$$\underset{(NT\times 1)}{\begin{bmatrix} y_1 \\ y_2 \\ \\ y_N \end{bmatrix}} = \underset{(NT\times 1)}{\begin{bmatrix} N_1 \\ 0 \\ \\ 0 \end{bmatrix}}\beta_{01} + \begin{bmatrix} 0 \\ N_2 \\ \\ 0 \end{bmatrix}\beta_{02} + \ldots + \begin{bmatrix} 0 \\ 0 \\ \\ N_N \end{bmatrix}\beta_{0N} + \underset{(NT\times 5)}{\begin{bmatrix} X_1 \\ X_2 \\ \\ X_N \end{bmatrix}}\beta_1 + \begin{bmatrix} u_1 \\ u_2 \\ \\ u_N \end{bmatrix}. \tag{5}$$

First apply OLS to (5). Denote the OLS estimates by $\hat{\beta}_1$ and $\hat{\beta}_{0i}$, i = 1, ..., N. Then σ_i^2 can be estimated by

$$\hat{\sigma}_i^2 = \frac{1}{T}(\mathbf{y}_i - \mathbf{N}_i\hat{\beta}_{0i} - \mathbf{X}_i\hat{\beta}_1)'(\mathbf{y}_i - \mathbf{N}_i\hat{\beta}_{0i} - \mathbf{X}_i\hat{\beta}_1), \tag{6}$$

and γ in equation (2) can be estimated by

$$\hat{\gamma} = \left[\sum_{i=1}^{N}\mathbf{Z}_i'\mathbf{Z}_i\right]^{-1}\left[\sum_{i=1}^{N}\mathbf{Z}_i'\hat{\beta}_{0i}\right]. \tag{7}$$

Given these results, an estimate of the error terms is obtained by

$$\hat{\eta}_i = \hat{\beta}_{0i} - \mathbf{Z}_i\hat{\gamma}, \tag{8}$$

which can be used to estimate the variance-covariance matrix, λ_i, given the assumption that this matrix is homoskedastic (identical for all plots):

$$\hat{\lambda} = \frac{1}{N}\sum_{i=1}^{N}\hat{\eta}_i\hat{\eta}_i'. \tag{9}$$

The estimates of σ_i^2 and λ, can then be substituted into the variance-covariance matrix $\mathbf{\Omega}_i$ in equation (4) to obtain GLS estimates of the β_1 and γ.

The Random Coefficient Estimation Results

The GLS estimates of β_1 and γ are shown in Table 1. The coefficients associated with rotation history (RI1, RI5 and CRI) are all statistically significant at the 1% level and have the signs indicated by production theory. In particular, the negative signs of the RI coefficients indicate that if an N-demanding crop such as corn is planted at time t, then a decrease in corn yield is expected at times t+i, i=1, 2, 3, … , as well. In addition, the effects of crop rotation at time t on corn yields at time t+i diminish as i increases, as shown by the declining size of the RI coefficients. These estimates offer an initial view of the dynamic effects of rotations on yields.

The negative coefficient estimates for the deviations of growing degree days (GDDDEV) and precipitation (PRECDEV) imply the expected presence of quadratic and concave relationships between corn yields and weather conditions. The coefficients for dummy variables for corn varieties increase with a few exceptions as relatively new corn varieties are applied (the omitted dummy is 11, the second oldest variety).

By substituting $\hat{\gamma}$ into equation (2), we can recover the random coefficient β_{0i}, which represents the marginal effect of N fertilizer application on yield conditional on plot-specific characteristics. Although the lack of statistical significance of the estimated coefficients of ZRI1 and ZRI5 weakens the reliability of these marginal productivity coefficient estimates, these estimates can be combined with the other parameter estimates to provide useful information about the marginal productivity differentials of N fertilizer on yields conditional on crop and plot-specific effects. The results are summarized in Figure 2 (which will be compared later with a similar estimate derived from the other model).

Figure 2 shows that the marginal contribution of N fertilizer has the highest value in the case of a continuous corn rotation, and that its marginal contribution to yield declines as N-fixing crops such as alfalfa are included in the rotation. In the continuous alfalfa rotation, the marginal yield effect of N is negative. This result is supported by experimental data showing declining corn yields at high fertilizer levels on plots with two or three successive alfalfa rotations.

The estimation results in Table 1 can also be used to predict yield conditional on crop rotations and N fertilizer application, and thus to shed light on the substitutability of N fertilizer and soil quality. Using mean weather conditions and the corn variety of 1994, along with the coefficient estimates, a simulation shown in Figure 3 portrays yield differentials conditional on different rotations. In year 6, after five years of continuous corn and five years of continuous alfalfa rotation, the predicted corn yield gap is equal to approximately 40 bushels/acre for an N fertilizer application level of 100 pounds/acre on corn. These simulation results also reflect average yield data for different rotations in the experimental data set.

The long-term substitutability of N fertilizer for land productivity is explored in the three panels of Figure 4, which show the effects of rotation on predicted yields at four different N application levels after 5, 10 and 30 years of distinct rotations. One can easily see that N fertilizer is at least a short-run substitute for land productivity: the year 6 yield difference between continuous corn and other rotations is substantially smaller at higher N application levels. Yet, as the second and third panels reveal, higher N application rates cannot compensate for productivity losses associated with long-term crop rotations. In percentage terms, while N application at 200 pounds/acre can decrease the yield difference between continuous corn and continuous alfalfa by 55% after 5 years, the same application rate can only reduce the gap by 9% after 30 years of the same rotations. The results summarized in Figure 4 cast significant doubt on the view that N fertilizer can act as a substitute for soil quality in the long run.

A Dynamic Structural Model for Recovering a Measure of Soil Quality

In this section we develop a recursive dynamic model of corn production and use it to recover an explicit measure of soil quality. Such a general measure should, in principle, provide fuller and more comparable information about the dynamics of soil quality with respect to key control variables than would proxy measures, thereby providing an explicit basis for incorporating soil quality as a state variable in dynamic economic analyses of land productivity, land markets, and conservation programs.

The recursive dynamic model involves two equations and has a simple design. Let f(·) denote a crop production function and g(·) the function that governs the state equation for soil quality. Then the nested production function can be written as:

$$Y_t = f(Q_t, N_t, Prec_t, G_t)\text{, and} \tag{10}$$

$$Q_t = g(Q_{t-1}, R_{t-1}), \tag{11}$$

where Y_t is (again, corn) yield at time t, Q_t is the state of soil quality at the start of period t, N_t is the level of N fertilizer application, $Prec_t$ is the average July precipitation, G_t is July growing degree days at year t, and R_{t-1} is the rotation index variable at year t-1.[1] The soil quality state equation says that the soil quality at the start of period t is a function of soil quality at the start of period t-1 and the rotation index at t-1 (which as above includes crop choice and N carryover). This specification reflects the recursive nature of soil quality evolution; i.e., soil quality at a certain period cannot be entirely determined by choosing the level of control variables in the previous period.

To estimate the soil quality state equation, we need to recover the parameters that govern (11) given the functional form of g(·). Substituting equation (11) into equation (10) gives a potentially estimable nested production function:

$$Y_t = f(g(Q_{t-1}, R_{t-1}), N_t, Prec_t, G_t)\,. \qquad (12)$$

The next step is to choose the functional forms of f(·) and g(·). Because the elasticity between soil quality and N fertilizer in (10) is a key issue in the analysis, the functional form for f(·) is chosen seeking minimal *a priori* restrictions on the substitutability of these two variables. The translog production function, which expresses the logarithm of output as a generalized quadratic function of the logarithm of inputs, satisfies these requirements. The production function f(·) then becomes

$$\ln Y = a_0 + \sum_i b_i \ln \mathbf{X}_i + \frac{1}{2}\sum_i \sum_j b_{ij} (\ln \mathbf{X}_i)(\ln \mathbf{X}_j)\,, \qquad (13)$$

where $\mathbf{X} = [Q_t, N_t, Prec_t, G_t]$ is a vector of input variables.

Given the translog assumption on the production function, a Cobb-Douglas structure for g(·) gives the necessary linearity in parameters that leave the model tractable. As is well known, the Cobb-Douglas structure imposes strong restrictions on the elasticity estimates of the governing state equation, an issue we explore below when discussing the model's results. After logarithmic transformation and successive substitution of Q_t, the state equation g(·) becomes

$$\ln Q_t = \sum_{j=1}^{24} \alpha^{j-1} \beta \ln R_{t-j} + \alpha^{24} \ln Q_{t-24}\,, \qquad (14)$$

where the initial soil quality (Q_{t-24}) is normalized to unity to reflect initial conditions when the sample is large and $\alpha < 1$. The final step involves substituting (14) into (13) to derive a nested production function which depends only on the observed variables. This non-linear function can then be estimated to recover the parameters of interest (α and β) which govern the evolution of soil quality.

Any such dynamic estimation confronts an identification problem related to the parameters that define the state variable in the nested production function. Consider the following representation of the state equation before the successive substitution:

$$\ln Q_t = \delta Z^T , \tag{15}$$

where $\delta = [\alpha, \beta]$ and $\mathbf{Z} = [\ln Q_{t-1}, \ln R_{t-1}]$. The identification problem is evident if we substitute (15) into (13), and observe the first two terms of the expression

$$\begin{aligned} \varepsilon_1 \ln Q_t &= b_1 \boldsymbol{\delta} \mathbf{Z}^T \\ \varepsilon_{11}(\ln Q_t)(\ln Q_t)^T &= b_{11}(\boldsymbol{\delta} \mathbf{Z}^T)(\mathbf{Z} \boldsymbol{\delta}^T), \end{aligned} \tag{16}$$

where ε_{ij}'s are the estimated coefficients. The identification problem arises because it is impossible to separate b_1 from δ and therefore recover the parameters of interest (α and β) from ε_1 without imposing a restriction on the value of b_1. Setting $b_1 = 1$ resolves the identification problems for the rest of the system. While this normalization changes the *absolute* value of the coefficients of the nested production function, it leaves their *relative* values unaffected, allowing us to estimate an ordinal measure of soil quality from the derived estimate of δ.[2]

The nested production function was estimated using NLS (Non-linear Least Squares) method, and the terms for a dozen categorical variables were added to control for changing seed varieties in the specification. Also, because sample information is not rich enough to estimate the coefficient b_{11} because of collinearity between ln Q_t and its square term ($(\ln Q_t)^2$), the latter term is dropped from estimating equation. The results are presented in Table 2, and as explained below they have the expected signs, a high level of significance, and explain 56% of the variation in corn yields. Some of the difference in R^2 values across the two models may be a result of the structural restrictions imposed on the structural model. It is a well-known fact that a structural model tends to provide richer explanations about the dynamics of the underlying variables, however the structural assumptions may reduce the overall explanatory power of the model.

The Dynamics of Soil Quality

The parameter estimates governing the dynamics of soil quality (α, β) are recovered with sensible values and high levels of significance. The estimate of α reflects the dynamic effects of crop rotation on soil quality over time, and its value of 0.647 means that the effects will decrease as time elapses. The estimated coefficient of the rotation index, β, is equal to -0.058. Because N uptake is measured positively, this negative value confirms the expectation that soil quality decreases with more intensive cultivation.

Other key regression coefficient estimates provide further insights into the soil quality-productivity nexus. The coefficient estimate on N (0.097) reflects a positive impact of N use on yield, controlling for other inputs. The negative value on the quadratic term of N application (-0.005) suggests that marginal productivity of N on corn yields declines at higher N application levels; however, this term lacks statistical significance. It is also interesting to consider the coefficient on the interaction term of soil quality and N fertilizer levels ((ln Q)(ln N)). The negative and statistically significant coefficient of this term (-0.242) indicates that there is an inverse relationship between the marginal productivity of N and soil quality. Derived from the nested production function, the marginal productivity of N as a function of soil quality is:

$$\frac{\partial y}{\partial N} = \frac{Y}{N} \cdot \left(0.097 - 0.005 \ln N - 0.242 \ln Q - 0.003 \ln G + 0.001 \ln P\right). \qquad (17)$$

Holding the other variables constant at their mean values, the marginal productivity of N conditional on soil quality is readily calculated. Soil quality is recovered using the estimation results (α and β) as discussed above, based on the results of four distinctive rotations over 20 years. An initial soil quality level is chosen, and then the four rotations ranging in terms of N uptake from continuous corn to continuous alfalfa are used to generate different soil quality outcomes. These range from a low of 0.85 for continuous corn to a high of 2.05 for continuous alfalfa. Then, the marginal productivity of N use on corn production is estimated for different levels of soil quality. The results are given in Figure 5, and (as was shown in Figure 2) the marginal productivity of N given lower soil quality (represented by continuous corn) is higher than that of better soil qualities (represented by other rotations). Because alfalfa fixes nitrogen, in alfalfa-intensive rotations such as CCCMM and MMMMM, additional nitrogen applications may reduce the yield of the subsequent corn crop. In these cases, the Cobb-Douglas structure implies that the marginal yield reduction due to overfertilization is greatest at lower N application rates.

In Kim *et al.*, the soil quality coefficient estimates were also used to examine the evolution of soil quality conditional on crop rotation and N application rates. We found that while rotations can be used to sustain or even improve soil quality, the same is not true for fertilizer applications. Soil quality drops off quickly with continuous corn rotations, and higher levels of fertilizer provide only minimal improvement.

Will Improved Soil Quality Measures Improve the Performance of Land Markets?

If the findings from the two models are reliable, then rotations provide a long-run basis for maintaining soil quality and productivity that fertilizer cannot. Whether this finding has relevance to the performance of land markets depends essentially on two factors, the degree to which soil quality information is imperfectly observed by buyers or demonstrated by sellers, and the length of time required to recover soil quality through rotational use of crops like alfalfa. Our two models give us the capability to explore this latter question, that is, to see whether the recovery time of soil quality or production is long enough that missing soil quality information could be of substance. Put differently, if one or two years of alfalfa rotation is sufficient to fully recover soil quality even when land has been in continuous corn for many years, then imperfect information on soil quality is less likely to be important than if recovery periods are more substantial.

We use the estimation results of the two models to evaluate the trajectory of soil quality recovery through the use of alfalfa. In Figure 6, two trajectory maps trace out the recovery time following continuous corn rotations of different lengths. In the upper graph, the estimation results from the RCM are mapped: these show declining yields over time under continuous corn, and progressively longer yield recovery periods. After five years of continuous corn, one year of alfalfa restores potential corn yields to base values, but after twenty years the full recovery threshold is in the third year. After thirty years of continuous corn, full recovery takes four years. The longer recovery time is due to the continuing yield decline in continuous corn. These results suggest that knowing a lengthy history of management practices could help buyers to evaluate potential land purchases.

The second graph maps out the recovery of soil quality using the dynamic structural model, but does so for only two cases, after five and twenty years of continuous corn. In this case, the decline in soil quality associated with corn production appears to occur almost entirely within the first five years, so that the recovery time in later years is only marginally different. In both time periods, soil quality takes about three years to recover, so that less information on key control variables would be required to signal underlying soil quality to other land market participants.

There is clearly a fundamental difference between the two trajectories in terms of their speed of decline. The Cobb-Douglas structure of the $g(\cdot)$ function and the estimated value of α from the dynamic structural estimation provide the basis for the rapid decline and then flat portion of the trajectory, while the less restrictive RCM functional form provides a more intuitive depiction of declining yields over time that then take progressively longer periods to regenerate. Two basic conclusions emerge. First, the more rigid structure needed to keep the dynamic soil quality model econometrically tractable may impose restrictions that limit the uses of the results for extensive modelling simulations. Second, both models show that missing information on soil quality could be important, in that the recovery time for soil quality regeneration following continuous corn cultivation could be economically important. It is still possible that other market signals or information already serve as proxies for observations on soil quality such as those generated in this study. However, given the dynamic nature of the evolution of soil quality and the potential for spatial variation in soil quality evolution, it is not obvious what those proxies might be.

Summary and Conclusions

In this paper, we have examined the relationship between soil quality, crop rotation, fertilizer use, and productivity. First, we developed a reduced-form, random-coefficients model of the relationships among crop rotations, N fertilizer application and corn yield. Estimation results showed that the marginal contribution of N fertilizer varies with a different rotation history; it has the highest value in the case of continuous corn rotation and decreases as N-fixing crops such as alfalfa are included in the rotation. Extrapolations of the estimation results were used to evaluate yield differentials conditional on different rotations and the short and long-term effects of N fertilizer as a substitute for land productivity. The predicted yield differentials between continuous corn and continuous alfalfa tend to increase as the number of years of the rotation increases. More importantly, the extrapolations provide empirical evidence against N fertilizer as a substitute for corn-intensive rotations in the long run.

We then developed a recursive, dynamic, structural-form model that employs soil quality directly as one of the arguments in the production function in order to measure relationships among crop rotation, N fertilizer application and soil quality. Although only the productivity aspect of soil quality was explored, our dynamic structural model provides a way of constructing a measure for soil quality which could be utilized to explore environmental and health related aspects of soil quality and to identify the key control variables that govern these aspects of soil quality.

The results of our structural-form estimation of soil quality reveal only slight soil quality improvement when N fertilizer is applied in the case of continuous corn. This slight improvement is insignificant compared to rotation effects. We also find an inverse relationship between soil quality and the marginal productivity of N fertilizer. The results also show that soil quality will decrease substantially under continuous corn, but that it can be maintained at a steady level when alfalfa is included in the rotational sequence. In particular, soil quality appears to approach its upper or lower bound in a relatively short period (about 5 years). The extent to which this result is sensitive to the choice of functional form is a subject for further research.

Combined, the models provide convincing evidence that while N may provide a short-term substitute for soil quality, it cannot in the long run. Yet, rotational choices do provide such an option for maintaining soil quality and land productivity and also the means for restoring the quality of land that has been intensively cropped. The recovery time, however, depends on the history of land use choices, which makes knowledge of the evolution of soil quality potentially important to buyers.

By providing information on a key state variable, our soil quality measure could be used in a wide variety of dynamic models of farmer behavior concerning land use and soil conservation investments. Of course, any such modelling effort must confront the issue of soil quality observability and its effects on farmer's land use decisions. In particular, the asymmetric distribution of information about soil quality may influence the operation of land markets, and thus, through the price of land, condition farmers' optimal land use decisions. More generally, our analysis motivates an extension of the Akerlof model in which the properties of goods evolve dynamically over time, thus influencing the emergence and functioning of markets (Kim).

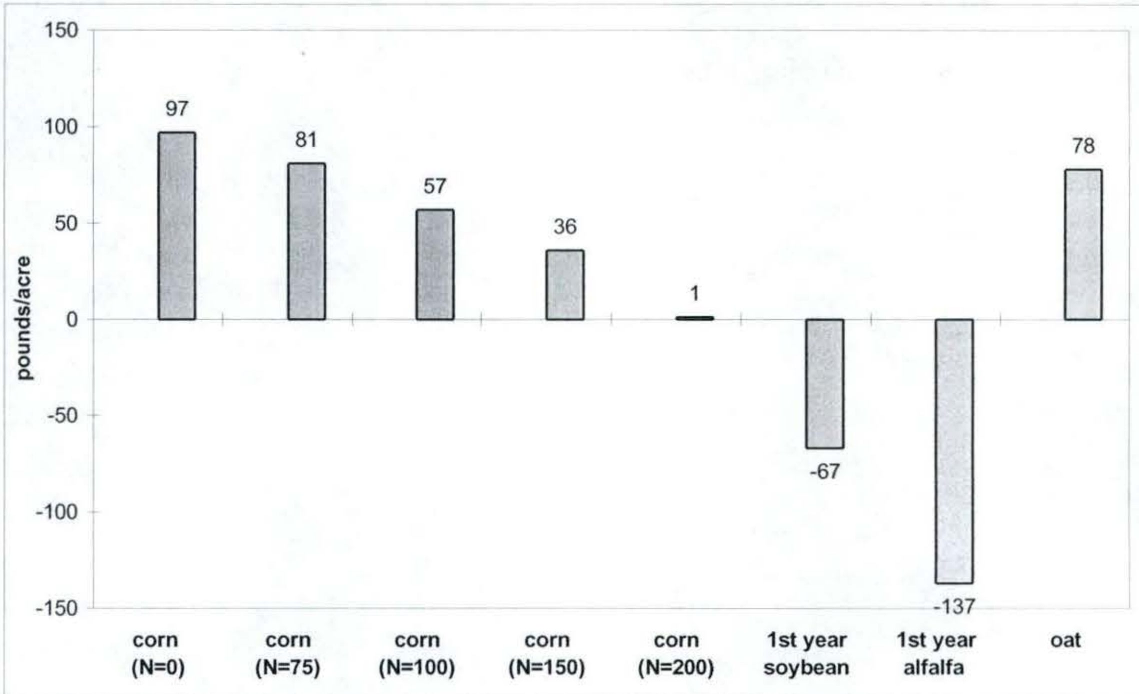

Figure 1. Net N uptake (pounds/acre) by crop, accounting for carryover from previous year. N fertilizer is applied only to corn. Figures in parentheses (e. g., N=150) indicate previous year's N application levels.

Table 1. Estimation of Random Coefficients Model for the Corn Production

Parameter	Coefficient	Standard Error
Constant	121.037	2.390***
RI1	-7.503	0.547***
RI5	-2.204	0.524***
CRI	-0.999	0.185***
GDDDEV (deviation from the mean)	-0.321	0.0342***
PRECDEV (deviation from the mean)	-4.767	0.895***
Dummy1	-6.692	3.275**
Dummy2	62.121	3.578***
Dummy3	19.527	5.106***
Dummy4	92.091	5.566***
Dummy5	29.357	3.502***
Dummy6	45.207	3.530***
Dummy7	10.442	3.342***
Dummy8	21.445	2.298***
Dummy9	0.373	4.452
Dummy10	-15.152	3.128**
Dummy12	35.655	4.855***
Dummy1988	-50.893	3.642***
ZIDEN (constant)	0.0245	0.011**
ZRI1	0.125	0.258
ZRI5	-0.0224	0.057

Note: Adjusted R^2 =0.965, number of observations = 1880. The symbols *, ** and *** denote significance at 10, 5, 1%, respectively. Dummy1988 was included in order to account for extremely dry weather conditions in 1988. The other dummies account for different corn varieties in the sample design. Corn output is measured in bu. ac^{-1} and N in $lbs.ac^{-1}$.

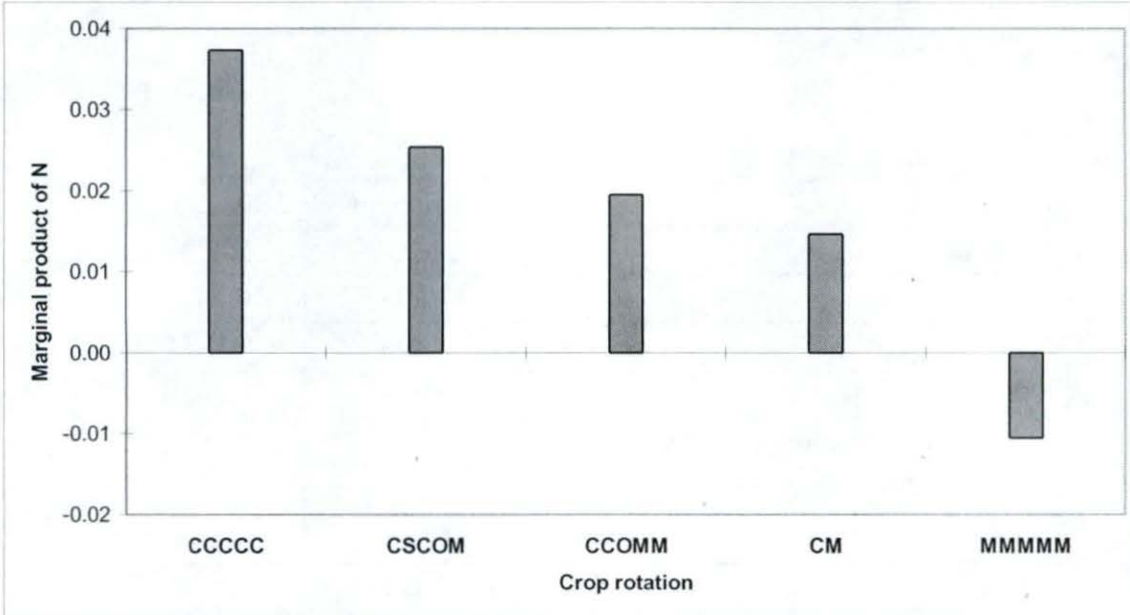

Figure 2. The marginal product of N fertilizer on corn conditional on crop rotations.

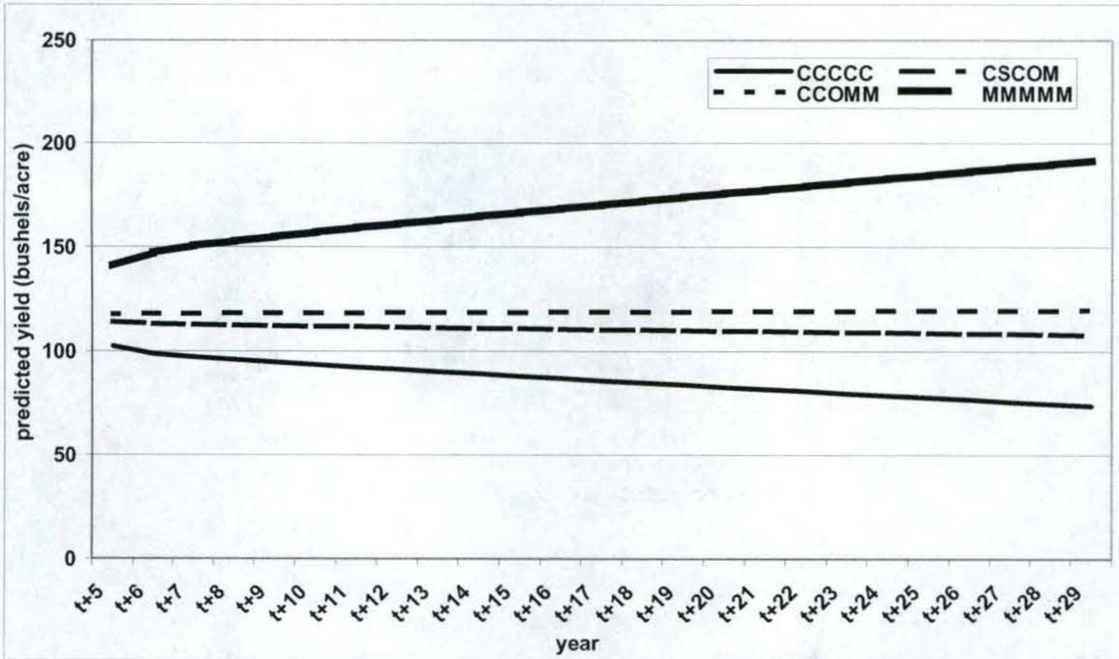

Figure 3. Corn yield differentials conditional on crop rotation (N=100 pounds/acre)

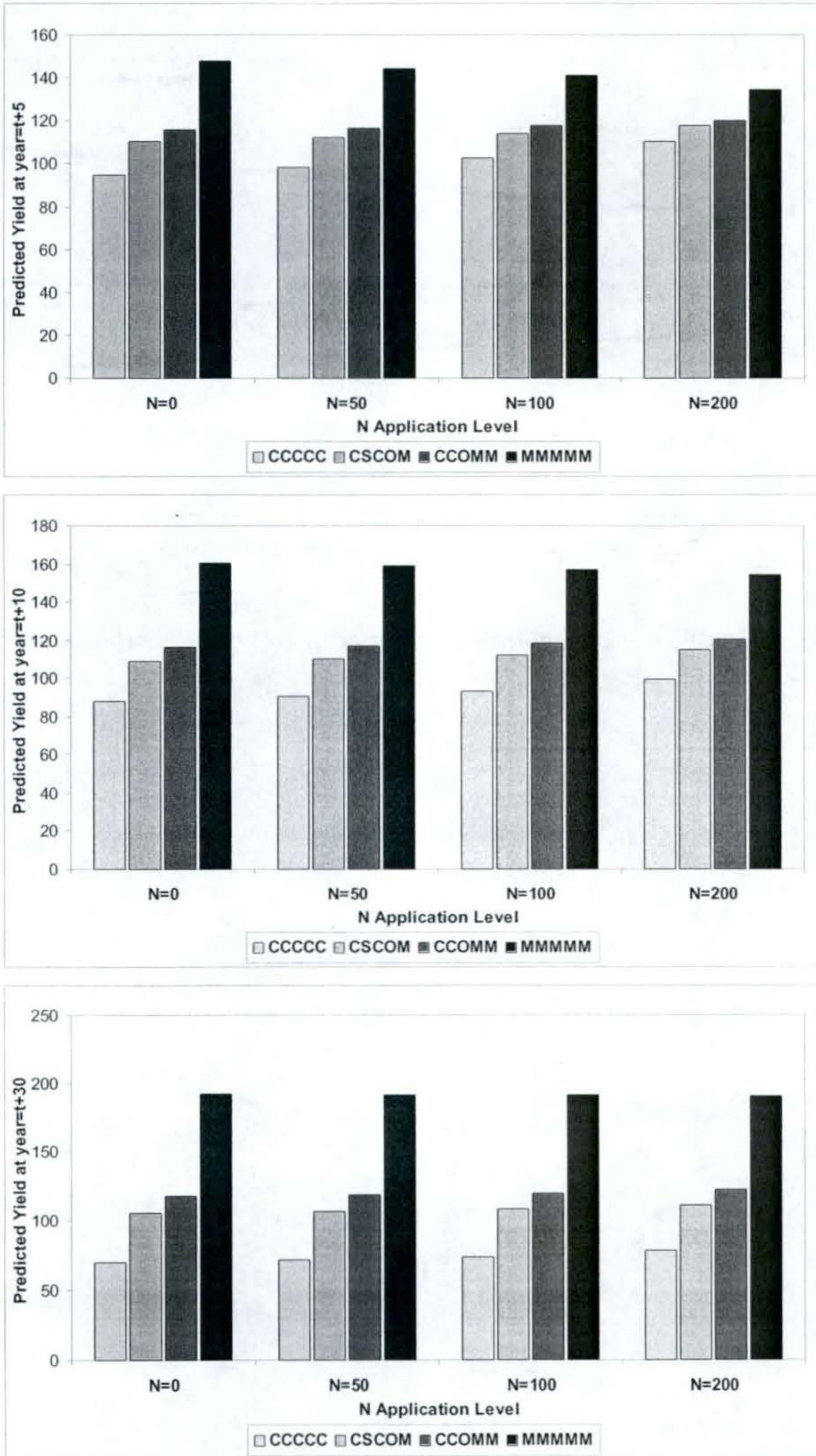

Figure 4. The effects of N application on predicted yields after 5, 10, and 30 years of given rotations.

Table 2. Estimated parameters of Translog Production Function (dependent variable = corn yields)

Parameter	Coefficient	Standard Error
Constant	-21.431	3.636***
α	0.647	0.029***
β	-0.058	0.024**
Log of N fertilizer (ln N)	0.097	0.038**
Log of July Precipitation (ln Prec)	2.080	0.456***
Log of July Growing Degree Days (ln G)	4.615	0.582***
$(\ln N)^2$	-0.005	0.005
$(\ln Prec)^2$	0.721	0.121***
$(\ln G)^2$	-.395	0.047***
(ln Q) (ln N)	-0.242	0.001***
(ln Q) (ln G)	-0.054	0.002*
(ln Q) (ln Prec)	-0.061	0.004***
(ln N) (ln G)	-0.003	0.003
(ln N) (ln Prec)	0.001	0.005
(ln G) (ln Prec)	-0.087	0.032***
Dummy1	-0.083	0.035**
Dummy2	0.262	0.088***
Dummy3	-0.683	0.099***
Dummy4	1.488	0.284***
Dummy5	0.288	0.036***
Dummy6	0.403	0.047***
Dummy7	0.126	0.037***
Dummy8	0.092	0.029***
Dummy9	-0.612	0.063***
Dummy10	-0.255	0.039***
Dummy12	-0.472	0.119***
Dummy1988	-0.717	0.047***

Note: Adjusted R^2 = .5606, number of observations = 1880. The symbols *, ** and *** denote significance at 10, 5, 1%, respectively. Corn output is measured in bu. ac^{-1} and N in lbs.ac^{-1}. For the description of the dummy variables see the caption of Table 1.

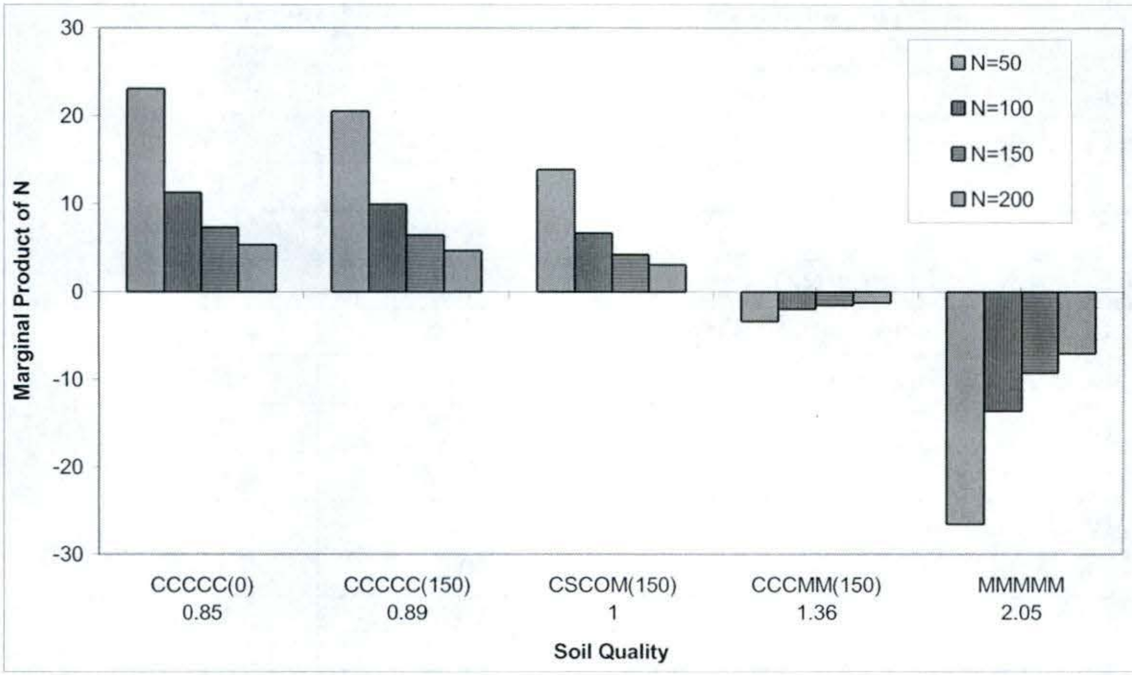

Figure 5. Relative marginal productivity of N fertilizer on corn conditional on soil quality. Data are grouped by rotation, and each group shows results for four levels of N application in the current year. Numbers in parentheses after each rotation (for example CCCCC(150)) show N application rate over the previous 20 years.

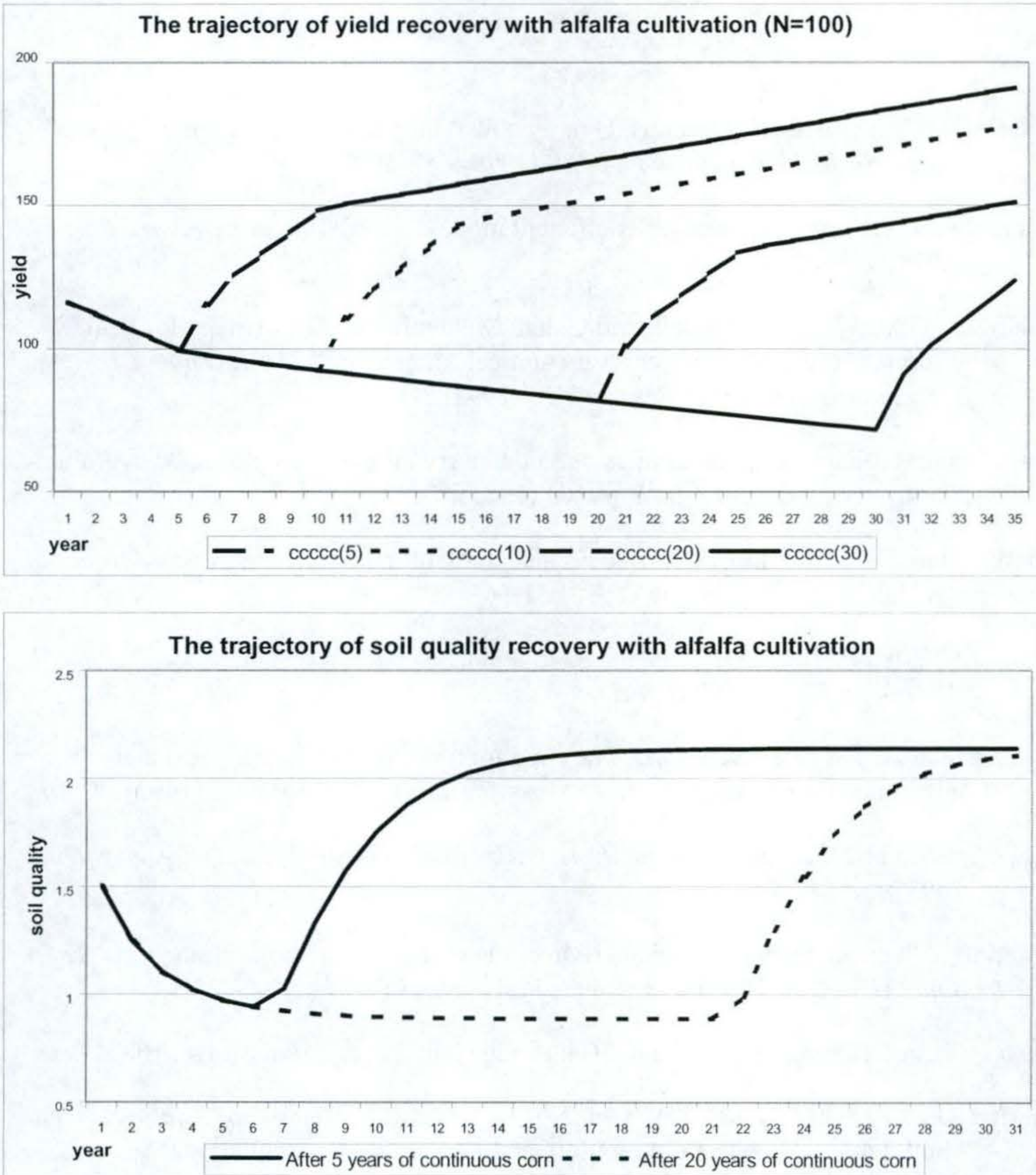

Figure 6. The trajectories of yield and soil quality recovery through the use of alfalfa

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Footnotes

1. For corn production, growing conditions for the month of July are critical since that is the month during which most pollination occurs (Hansen, 1991).

2. In some applications of this methodology the lack of pre-sample values of control variables would pose an econometric problem; when the time series is not very long, the treatment of the missing values is quite difficult (Greene). However, by construction the pre-sample values of the control variable in our case, R_{t-j}, for all years but the most recent in the data set, are all zeroes, reflecting uniform initial soil quality across all plots.