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# Measuring soil quality dynamics A role for economists, and implications for economic analysis

Kwansoo Kim, Bradford L. Barham, Ian Coxhead*

*Department of Agricultural and Applied Economics, University of Wisconsin-Madison, Taylor Hall, 427 Lorch Street, Madison, WI 53706, USA*

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**Abstract**

Measuring soil quality is extremely difficult, yet it has clear economic importance. In particular, there is a great deal of empirical interest in the dynamics of soil quality evolution when land managers respond to policies and other incentives. Yet current methodologies for measuring changes in agricultural land quality are largely static and rely heavily either on incomplete measures such as proxy variables, or ad hoc indexes of selected soil characteristics. Moreover, much empirical work relies on static econometric techniques or simulation models. In this paper, we develop a means to infer soil quality changes from input and output data using a dynamic production function model. Using data from field experiments, we estimate the model in a way that allows the recovery of a dynamic measure of soil quality whose evolution depends on variations in management practices. Our methodology and findings will help provide firmer empirical foundations for analyses of the economic implications of land degradation and the soil quality implications of agricultural policies. © 2001 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

The possibility of long-term soil productivity degradation has potentially significant implications for economic welfare. An understanding of soil productivity dynamics thus has economic value, both as a tool for agricultural decision-making, and as an input to ex ante and ex post analyses of the benefits and costs of interventions, such as agricultural policies or R&D investments, that alter the value of crops, the uses of land, or cultivation practices. It is thus somewhat surprising that there is little empirical evidence on the dynamics of soil productivity that is both rigorous and usable for the purposes of economic and policy analysis. Repeated calls from soil scientists and others for empirical examinations of the dynamics of soil quality "in the context of land management strategies, interactions, and tradeoffs" have not been effectively addressed (Karlen et al., 1997; Jaenicke and Lengnick, 1999); nor has clear evidence from economists

* Corresponding author. Tel.: +1-608-262-6390; fax: +1-608-262-4376.
*E-mail address:* coxhead@facstaff.wisc.edu (I. Coxhead).

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of long-term soil productivity decline in some of the developing world's most agriculture-dependent economies (Byerlee, 1994; Cassman and Pingali, 1995; Ali and Byerlee, 2000) stimulated major advances on the underlying dynamics of soil quality.

Three types of problems have inhibited empirical research. First is the inherent observability issue. Any attempt to obtain a direct measure of soil quality confronts the choice of either arbitrarily selecting a single indicator such as soil depth (e.g., Burt, 1981), or the construction of an ad hoc index of indicators (e.g., Rhoton and Lindbo, 1997). Both approaches have been criticized for lacking rigorous foundation and reproducibility across heterogeneous soil conditions (e.g., Karlen et al., 1997). Second, data on the attributes of soils and on conditioning factors such as management techniques are difficult and expensive to collect, especially in the time series or panel format required for dynamic analysis. Third, there has been a tendency to rely on the use of elaborate but static simulation packages, such as EPIC, even by those with access to data suitable to dynamic analyses. [1]

In this paper, we introduce a parsimonious method to explain current soil productivity in terms of past management choices, and to predict its evolution under future choices. The core of the method is a dynamic structural model whose recursive properties are exploited to recover an indirect, but general, measure of soil productivity based on yields. As a result, the structure of the model enables explicit analysis of the relationship between soil productivity and key control variables, and offers an empirical method for estimating the parameters that govern these relationships. [2] Our goal here is to explore this technical relationship between soil productivity and key control variables. As such, we do not present a behavioral model that utilizes this technical relationship. Rather, by providing quantitative measures of a key state variable, soil productivity, our methods and findings have value as intermediate inputs to assessments of the causes and economic consequences of long-term declines in the quality of farmland used for intensive staple crop cultivation.

We use data from field experiments in which the primary intent was to study the effects of rotations and fertilizer application on yields, particularly of corn. Our models exploit these data to present a careful examination of how variations in rotation and fertilizer use affect the dynamics of soil productivity and crop yields. These models, depending on the type of field experiments undertaken, could also be used to explore the effects of other farm management practices on the dynamics of soil productivity or on other soil quality attributes. A novel feature of our approach is that it permits an explicit analysis of the recovery path of soil quality under alternative management regimes.

Although the central contribution of this paper is the dynamic econometric model, we preface its presentation with a more standard approach to analyzing yield response to nitrogen fertilizer and rotations, namely a random coefficients model (RCM). Next, we introduce and estimate the dynamic structural model using non-linear least-squares. Both models give statistically significant estimates of key parameters with expected signs, and confirm previously documented findings. We then use estimates from the models to evaluate the speed at which soil quality returns to base

[1] The EPIC model is a widely used modeling platform for simulating the interaction of the soil-climate–plant-management processes in agricultural production (Putman and Dyke, 1987). However, the parameters which drive the model are not estimated using dynamic statistical methods like those presented in this paper. Thus, these types of models cannot provide reliable predictions of how variations in management processes are likely to shape outcomes of interest. Instead, EPIC and other such simulation models offer scenarios for exploring the interaction of the many processes at work in these models. Future research efforts might well be aimed at trying to extend the dynamic framework developed in this paper in order to capture some of the richer detail of models like EPIC, and at the same time do so in a way that allows the underlying parameters to be estimated statistically.

[2] Soil and other natural scientists may find the proposed method unsettling, because the soil quality measure is recovered without making explicit use of measures of the physical, chemical, and biological properties of soils. In that sense, the measure is a complement to rather than a substitute for a unified, cross-cutting scientific model of soil quality. However, our approach is more coherent than previous soil quality measures. These commonly involve either the use of soil quality proxies, such as topsoil depth, organic matter content or water absorption potential (Burt, 1981; Walker, 1982; van Kooten et al., 1990; Rhoton and Lindbo, 1997), or the construction of a multivariate soil quality "index" using a battery of quantitative and qualitative indicator variables with unstated or arbitrary weights (Pierce et al., 1983; Smith et al., 1993; Karlen et al., 1997).

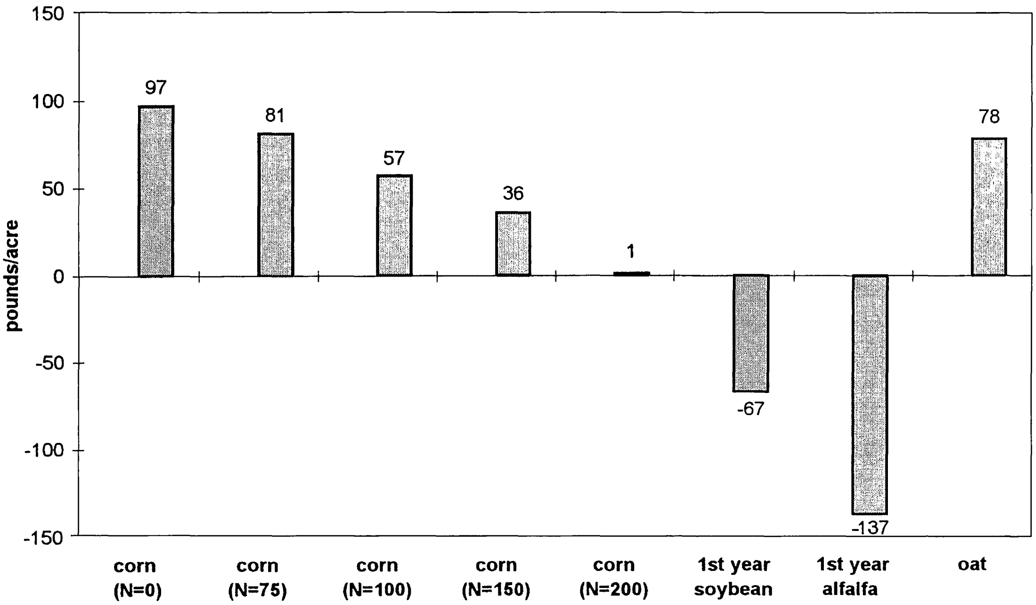


Fig. 1. Net N uptake (lb/acre) by crop, accounting for carryover from previous year. N fertilizer is applied only to corn. Figures in parentheses (e.g., $N$=150) indicate previous year's N application levels.

levels under alternative management regimes following a period of intensive grain cultivation. Finally, we discuss some applications and implications of our research for economic and policy analysis.

## 2. The data

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 tested include continuous corn (CCCCC), corn–soybeans–corn–oats–alfalfa (CSCOM), corn–corn–corn–alfalfa–alfalfa (CCCMM), corn–soybean (CS), corn–alfalfa (CM) and continuous alfalfa (MMMMM), and the usable data set spans from 1972 to 1995 (see Vanotti and Bundy, 1994; Kim et al., 2000, for further details).

Nitrogen fertilizer (N) is applied only to corn plots and at four distinct levels on sub-plots (0, 50, 100, and 200 lb/acre were applied from 1977 to 1995). Thus, two features of the experimental design shape the subsequent econometric specifications. First, rotation and N fertilizer use are the only variations in management practices (although new seed varieties were tried in different years), so our study focuses on how these practices affect the dynamics of soil quality and corn yields.[3] Second, since N is applied only to corn, measures of rotation and N use are strongly collinear. We resolve this problem by combining rotation choices and N levels into a single index of N uptake and carryover.

Construction of this index uses estimates of N uptake and carryover from the same data set (Vanotti and Bundy, 1994, 1995; Vanotti et al., 1995). In the case of legumes, nitrogen uptake is negative since these are N-fixing crops; the index also nets out N carryover from previous fertilizer applications (see Kim et al., 2000, for details). By construction, if no crops were planted on a given plot, the rotation–fertilizer index for that plot and year would be zero. Fig. 1 shows the average amount of N uptake after taking account of both the uptake effects of rotations and carryover

[3] Because tillage practices, liming, phosphates, and other management practices were uniformly administered during the experiment across all of the plots, no explicit estimates of their effects on soil quality can be recovered from the estimation.

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.

## 3. A random coefficients model

We first examine the short- and long-term effects of crop rotations and N use on corn yields using an RCM (Swamy, 1970; Hsiao, 1986). This approach is designed for use when the parameters of the estimated relationship may vary over time or space. Previous applications to agricultural production have used the RCM approach to obtain improved estimators in the presence of unobserved sources of variation such as rainfall or pests (e.g., Smith and Umali, 1985). However, the RCM is also a powerful and parsimonious technique to control for *known* fixed effects like past crop rotations that might have plot-specific impacts.

### *3.1. The RCM model*

Let $\mathbf{y}_i$ be a vector of time-series observations on corn yields for plot $i$, $\mathbf{N}_i$ a vector of time-series observations on the level of N fertilizer application for plot $i$, $\mathbf{X}_i$ a matrix of time-series observations of exogenous variables, $\boldsymbol{\beta}_1$ a vector of parameters, and $\boldsymbol{\epsilon}_i$ a vector of uncorrelated random variables with zero mean and variance–covariance matrix $E\boldsymbol{\epsilon}_i\boldsymbol{\epsilon}_j' = \sigma_{ij}^2\mathbf{I}_T$.

The RCM specification for corn-yield response is:

$$\mathbf{y}_i = \beta_{0i}\mathbf{N}_i + \mathbf{X}_i\boldsymbol{\beta}_1 + \boldsymbol{\epsilon}_i, \quad i = 1, \ldots, n, \tag{1}$$

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

where $\beta_{0i}$ is a random coefficient that varies according to (2). $\mathbf{Z}_i$ and $\boldsymbol{\gamma}$ in (2) are vectors of known and unknown constants, respectively, and $\eta_i$ is an unobservable random variable with zero mean and variance–covariance matrix $E\eta_i\eta_i' = \lambda_i$ and $E\eta_i\eta_j' = 0$. We assume that $\boldsymbol{\epsilon}_i$ and $\eta_i$ are uncorrelated. 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 $\beta_{0i}$. Thus values of variables in $\mathbf{Z}_i$ affect the marginal productivity of nitrogen fertilizer. Since the same information enters both the vector $\mathbf{Z}_i$ and the matrix $\mathbf{X}_i$, we now discuss the composition of each in turn.The matrix $\mathbf{X}_i$ includes variables representing the short-term and long-term effects of alternative crop rotations. Based on the N uptake information discussed above, we develop three rotation indexes for each year $t$ and each plot $i$. $R^1$, the current value of the index, equals the N uptake of the current period's crop plus the N fertilizer carryover. $R^5$, a 5-year moving summation of $R^1$, provides a measure of the short-term rotation history. $R^c$, the cumulative summation of $R^1$, is constructed to capture the long-term history. The vector $\mathbf{X}_i$ contains a constant term plus $R^1$, $R^5$, and $R^c$, the mean (absolute) deviation over $T$ years for July growing degree days (Gdev), the mean (absolute) deviation over $T$ years for July precipitation (Precdev),[4] dummy variables for different corn varieties (D1–D10, D12) used in the experiments, and a dummy variable (Dummy1988) for the year 1988, which was unusually dry.

$\mathbf{Z}_i$ represents plot-specific characteristics. It consists of a constant and $ZR_i^1$, the mean value of $R^1$, and $ZR_i^5$, the mean value of $R^5$ (both means are calculated in time $t$ over all previous periods). $\mathbf{Z}_i$ thus characterizes plot-specific information in terms of initial differentials or those that might arise as a function of past crop choices.

Combining Eqs. (1) and (2), the full specification is given by

$$\mathbf{y}_i = \mathbf{W}_i\boldsymbol{\gamma} + \boldsymbol{\beta}_1\mathbf{X}_i + \mathbf{u}_i, \tag{3}$$

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

$$\begin{bmatrix}\hat{\boldsymbol{\beta}}_1\\ \hat{\boldsymbol{\gamma}}\end{bmatrix}_{\mathrm{GLS}} = \left[\sum_{i=1}^{n}\begin{bmatrix}\mathbf{X}_i'\\ \mathbf{Z}_i'\mathbf{N}_i'\end{bmatrix}\boldsymbol{\Omega}_i^{-1}(\mathbf{X}_i, \mathbf{N}_i\mathbf{Z}_i)\right]^{-1} \times \left[\sum_{i=1}^{n}\begin{bmatrix}\mathbf{X}_i'\\ \mathbf{Z}_i'\mathbf{N}_i'\end{bmatrix}\boldsymbol{\Omega}_i^{-1}\mathbf{y}_i\right]. \tag{4}$$

Details of the derivation of this estimator are presented in Kim et al. (1997).

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

### 3.2. RCM estimation results

The GLS estimates of $\boldsymbol{\beta}_1$ and $\boldsymbol{\gamma}$ are shown in Table 1. The coefficients associated with rotation history ($R^1$, $R^5$ and $R^c$) are all statistically significant at the 1% level and have the signs indicated by production theory. In particular, negative signs of the $R^1$ coefficients indicate that if an N-demanding crop such as corn is planted at time $t$, then a decrease in corn yield can be expected at times $t+i$ ($i$>0), as well. In addition, the effects of the rotation at time $t$ on yields at time $t+i$ diminish as $i$ increases, as shown by the declining size of the $R^1$ 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 (Gdev) and precipitation (Precdev) imply quadratic and concave relationships between corn yields and weather conditions, as expected. 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). Only the estimated coefficients for $ZR_i^1$ and $ZR_i^5$ are not statistically significant.

Table 1
Estimation of RCM for the corn production[a]

| Parameter | Coefficient | S.E. |
|---|---|---|
| Constant | 121.037 | 2.390*** |
| $R^1$ | −7.503 | 0.547*** |
| $R^5$ | −2.204 | 0.524*** |
| $R^c$ | −0.999 | 0.185*** |
| Gdev (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** |
| $ZR^1$ | 0.125 | 0.258 |
| $ZR^5$ | −0.0224 | 0.057 |

[a]Note: adjusted $R^2$=0.965, number of observations=1880. 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 bushels/acre and N in lb/acre.

**Significance at 5%.

***Significance at 1%.

By substituting $\hat{\boldsymbol{\gamma}}$ into Eq. (2), we can recover the random coefficient $\beta_{0i}$, which provides information about the marginal productivity effects of N fertilizer on yields, conditional on crop and plot-specific effects. By constructing a 90% confidence interval around the mean estimates, we summarize the results obtained from the estimates of the first and second moments of marginal productivity of N fertilizer by rotation in Fig. 2. As shown, the expected value of the marginal contribution of N fertilizer has the highest value in the case of a continuous corn rotation, and the marginal contribution of N to yield declines as N-fixing crops such as alfalfa are introduced in the rotation. The marginal product of N fertilizer turns out to be statistically significant at 10% and 5% level for the continuous corn and CSCOM rotation, respectively. Under a continuous alfalfa rotation, the marginal yield effect of N is statistically insignificant suggesting that when a plot is already in good growing condition, an additional N fertilizer would not produce any significant yield effects. 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 variance of the marginal yield effect of N fertilizer in the continuous corn rotation is greater than in the other rotations involving corn, and also confirms a common assumption in the production literature that N fertilizer is a risk-increasing input. More generally, since these variance estimates provide a measure of the marginal output risk associated with fertilizer inputs across different rotation practices, they could be useful in behavioral models concerned with producer rotation and fertilizer application decisions under risk.

The results in Table 1 can also be used to predict yield conditional on rotation and N application, and thus to shed light on the substitutability of fertilizer and soil quality. Using mean weather conditions and the corn variety of 1994, along with the coefficient estimates, a simulation shown in Fig. 3 portrays yield differentials conditional on different rotations. In year 6, after 5 years of continuous corn and 5 years of continuous alfalfa rotation, the predicted corn yield gap is

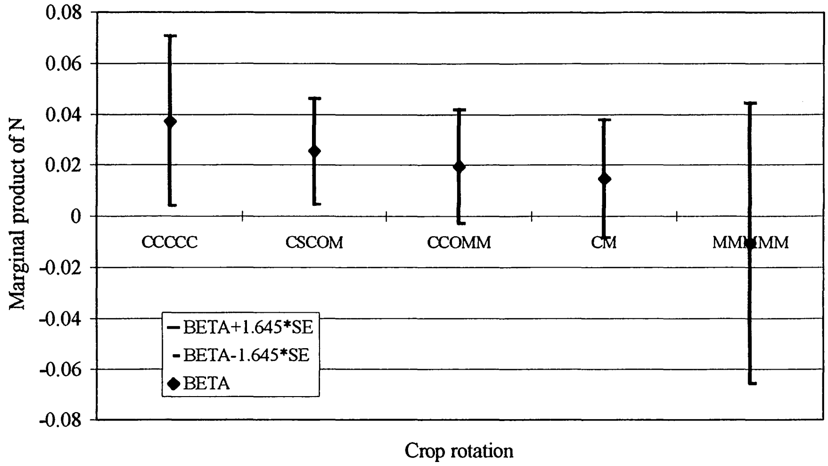


Fig. 2. The 90% confidence interval of the marginal product of N fertilizer on corn conditional on crop rotation. BETA indicates the expected value of marginal product of N and SE stands for standard error associated with its expected value.

equal to approximately 40 bushels/acre (2517 kg/ha) for an N-fertilizer application level of 100 lb/acre (112 kg/ha) 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 Fig. 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

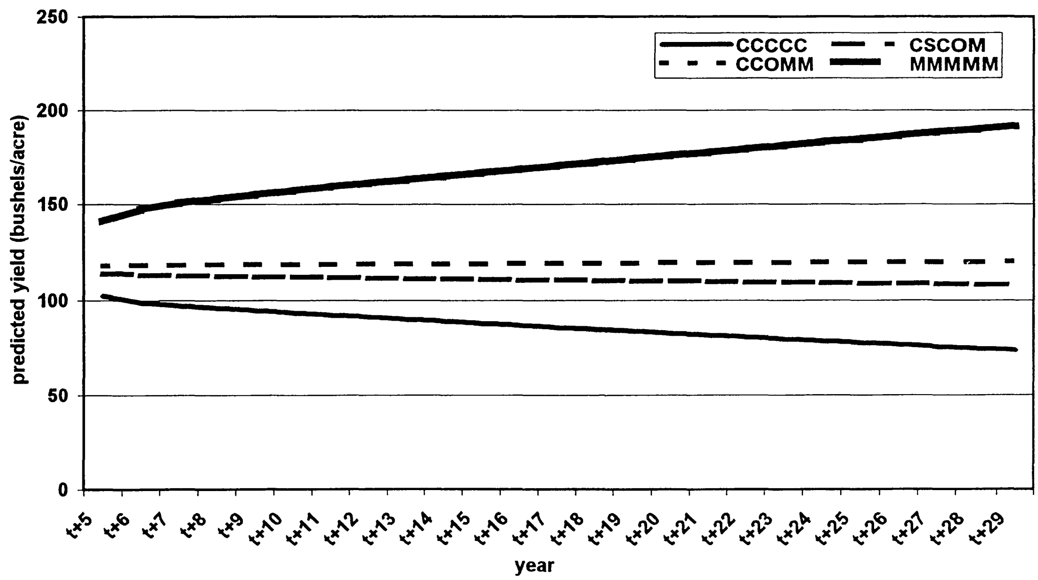


Fig. 3. Corn yield differentials conditional on crop rotation ($N$=100 lb/acre).

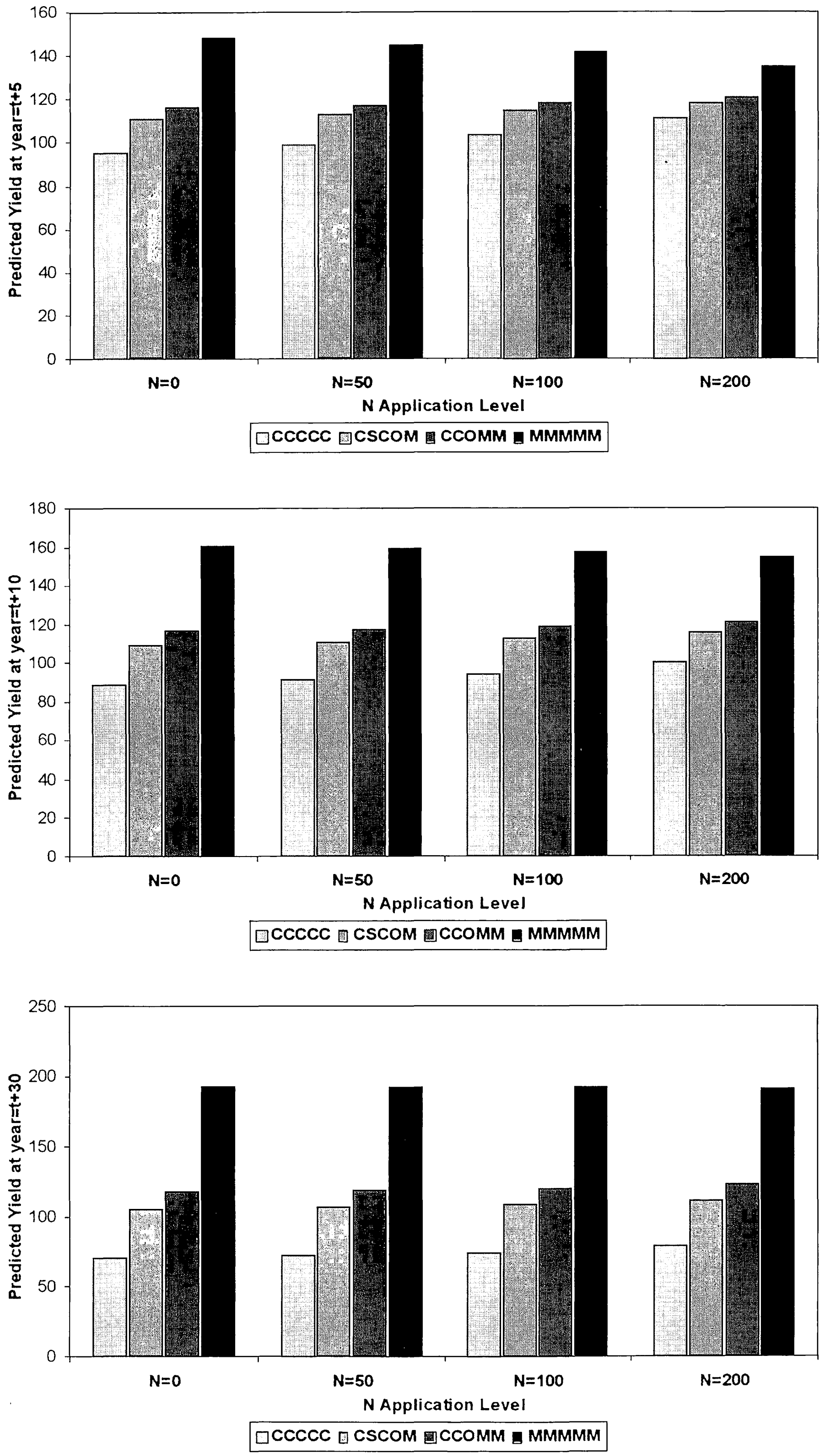


Fig. 4. The effects of N application on predicted yields after 5, 10, and 30 years of given rotations.

long-term crop rotations. In percentage terms, while N application at 200 lb/acre can decrease the yield difference between corn grown after continuous corn rotation and a continuous alfalfa rotation 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 Fig. 4 cast significant doubt on the view that N fertilizer can act as a substitute for soil quality in the long run, even when applied at very high rates.

## 4. A dynamic structural model

While the RCM approach uncovers some agronomic relationships and some soil productivity dynamics, it does not yield an explicit measure of soil quality. In this section, we develop a recursive dynamic model of corn production with the aim of recovering just such a measure. Such a general measure should, in principle, reveal more about the dynamics of soil quality with respect to key control variables than would proxy measures used in previous efforts. Moreover, since our measure uses the type of data that are available in many locales, it should allow for comparisons across sites. We regard our measure as providing an explicit means to incorporate soil quality as a state variable in dynamic analyses of land productivity, land markets, and conservation programs.

### 4.1. The structural model

Suppose soil quality were observable, and that its value at a given time depended on land management practices and its value in the previous period. Then, letting $f(\cdot)$ denote a crop production function and $g(\cdot)$ be the function that governs the state equation for soil quality, a nested production function could be written as:

$$Y_t = f(Q_t, N_t, \mathrm{Prec}_t, G_t), \tag{5}$$

$$Q_t = g(Q_{t-1}, R^1_{t-1}), \tag{6}$$

where $Y_t$ is (again, corn) yield at time $t$, $Q_t$ the state of soil quality at the start of period $t$, $N_t$ the level of N fertilizer application, $\mathrm{Prec}_t$ the average precipitation, $G_t$ the growing degree days at year $t$, and $R^1_{t-1}$ is the rotation index variable at year $t-1$.[5] The soil quality state equation (6) 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 includes crop choice and N carryover as above). 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 (6) given the functional form of $g(\cdot)$. Substituting Eq. (6) into Eq. (5) gives a potentially estimable nested production function:

$$Y_t = f(g(Q_{t-1}, R^1_{t-1}), N_t, \mathrm{Prec}_t, G_t). \tag{7}$$

The next step is to choose the functional forms of $f(\cdot)$ and $g(\cdot)$. Since the elasticity between soil quality and N fertilizer in (5) is a key issue in the analysis, we seek the functional form for $f(\cdot)$ that imposes 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 $f(\cdot)$ then becomes

$$\ln Y = a_0 + \sum_i b_i \ln \mathbf{X}_i + \frac{1}{2}\sum_i \sum_j b_{ij} (\ln \mathbf{X}_i)(\ln \mathbf{X}_j), \tag{8}$$

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

Given the translog assumption on the production function, a Cobb–Douglas structure for $g(\cdot)$ 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 $g(\cdot)$ becomes

$$\ln Q_t = \sum_{j=1}^{24} \alpha^{j-1} \beta \ln R^1_{t-j} + \alpha^{24} \ln Q_{t-24}, \tag{9}$$

[5] In the empirical model $\mathrm{Prec}_t$ is the average July precipitation and $G_t$ is the July growing degree days.

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 (9) into (8) 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 ($\alpha$ and $\beta$) 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:

$$\ln Q_t = \boldsymbol{\delta}\mathbf{A}', \tag{10}$$

where $\boldsymbol{\delta}=[\alpha, \beta]$ and $\mathbf{A} = [\ln Q_{t-1}, \ln R^1_{t-1}]$. The identification problem is evident if we substitute (10) into (8), and observe the first two terms of the expression

$$\zeta_1 \ln Q_t = b_1\boldsymbol{\delta}\mathbf{A}',$$
$$\zeta_{11}(\ln Q_t)(\ln Q_t)' = b_{11}(\boldsymbol{\delta}\mathbf{A}')(\mathbf{A}\boldsymbol{\delta}'), \tag{11}$$

where $\zeta_{ij}$'s are the estimated coefficients. The identification problem arises because it is impossible to separate $b_1$ from $\boldsymbol{\delta}$ and therefore recover the parameters of interest ($\alpha$ and $\beta$) from $\xi_1$ 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 $\boldsymbol{\delta}$.[6]

The nested production function was estimated using NLS (non-linear least-squares) method.[7] The results are presented in Table 2, and 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 although structural models tend to provide richer explanations about the dynamics of the underlying variables, their structural assumptions may reduce the overall explanatory power of the model.

Table 2
Estimated parameters of translog production function (dependent variable=corn yields)[a]

| Parameter | Coefficient | S.E. |
|---|---|---|
| Constant | −21.431 | 3.636*** |
| $\alpha$ | 0.647 | 0.029*** |
| $\beta$ | −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 |
| $(\ln \text{Prec})^2$ | 0.721 | 0.121*** |
| $(\ln G)^2$ | −0.395 | 0.047*** |
| $(\ln Q)(\ln N)$ | −0.242 | 0.001*** |
| $(\ln Q)(\ln G)$ | −0.054 | 0.002* |
| $(\ln Q)(\ln \text{Prec})$ | −0.061 | 0.004*** |
| $(\ln N)(\ln G)$ | −0.003 | 0.003 |
| $(\ln N)(\ln \text{Prec})$ | 0.001 | 0.005 |
| $(\ln G)(\ln \text{Prec})$ | −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*** |

[a]Note: adjusted $R^2$=0.5606, number of observations=1880. Corn output is measured in bushels/acre and N in lb/acre. For the description of the dummy variables, see the caption of Table 1.
*Significance at 10%.
**Significance at 5%.
***Significance at 1%.

[6] 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, 1993). 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.

[7] As before, 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 the estimation equation.

### 4.2. Structural model estimates

The parameter estimates governing the dynamics of soil quality ($\alpha$, $\beta$) are recovered with reasonable values and high levels of significance. The estimate of $\alpha$ reflects the dynamic effects of crop rotation on soil quality over time, and its value (0.647) means that the effects will diminish as time elapses. The estimated coefficient of the rotation index, $\beta$, 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 the 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

$$\frac{\partial y}{\partial N} = \frac{Y}{N}(0.097 - 0.005 \ln N - 0.242 \ln Q - 0.003 \ln G + 0.001 \ln \mathrm{Prec}). \tag{12}$$

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 ($\alpha$ and $\beta$) 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 Fig. 5, and (as shown

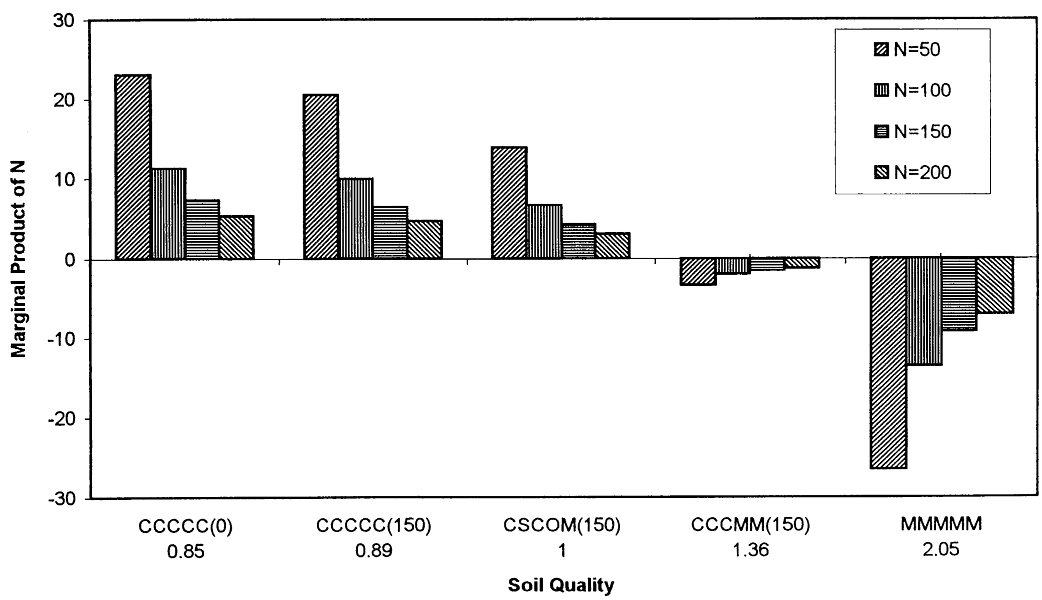


Fig. 5. Relative marginal productivity of N fertilizer on corn conditional on soil quality. Data are grouped by rotation, and each group shows results for four levels of N application in the current year. Numbers in parentheses after each rotation (e.g., CCCCC(150)) show N application rate over the previous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

in Fig. 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). Since alfalfa fixes nitrogen, in alfalfa–intensive rotations such as CCCMM and MM-MMM, 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. (2000), 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. This finding (along with the RCM results) contradicts those of some previous studies in the economic literature on soil quality. In particular, it provides no support in the case of corn for the widely applied conclusion of Burt (1981) that "intensive wheat production with good cultural and fertilizer practices, etc., is not a threat to the long-run productivity of soils". [8]

## 5. Implications for economic analysis

If the findings from the two models are reliable, then rotations of N-using and N-fixing crops provide a long-run basis for maintaining soil productivity that fertilizer alone cannot. The importance of this result for private land management practices and agricultural policies depends on three conditions: the length of time required to restore soil quality through rotational practices; the relative economic returns to N-using and N-fixing crops; and the degree to which soil quality and its expected trajectory are reflected in the agricultural land market. If soil quality recovery takes time and the economic returns to N-fixing crops are relatively low, then the efficiency effects associated with the rotation-fertilizer tradeoff just mentioned could be important. This is especially true if the tradeoff is not reflected in land valuations, e.g., if soil quality dynamics are not readily observable (Kim and Chavas, 1999). Our two econometric models give us the opportunity to explore the first of these conditions, i.e., the recovery time of soil quality under alternative rotations. Subsequently, we comment on the other two conditions.

### 5.1. Soil quality recovery paths

In Fig. 6, two trajectory maps trace the recovery time of productivity and soil quality following continuous corn rotations of different lengths. The upper graph displays the estimation results from the RCM: these show declining yields over time under continuous corn, and progressively longer yield recovery periods under alfalfa. After 5 years of continuous corn, 1 year of alfalfa restores potential corn yield to its initial value, but after 20 years, the full recovery takes 3 years and after 30 years of continuous corn, recovery takes 4 years. The longer recovery time is due to the progressive yield decline in continuous corn. These results provide information that has value to land managers and for the design of soil conserving rotational patterns. Knowing a lengthy history of crop choices could also help potential buyers to evaluate land purchases in cases where soil quality information is not otherwise readily observable and where economic returns to alternate crops are significantly less than to the principal crop.

The lower graph uses the results of the dynamic structural model to show the recovery path of soil quality after 5 and 20 years of continuous corn. In both cases, the estimated decline in soil quality associated with corn production appears to occur almost entirely within the first 5 years, and soil quality recovery takes about 3 years. If these estimated soil quality recovery paths are accurate, then land managers and market participants might care about previous cropping patterns, but would need less historical information than the RCM results suggest.

The RCM model and the dynamic structural model provide somewhat different views of the rates of decline of productivity and soil quality under continuous corn and the subsequent recovery paths under alfalfa. These differences appear to derive from the Cobb–Douglas structure of the $g(\cdot)$ function and the

[8] Concern about the substitutability of fertilizer for soil quality has been a matter of debate (Burt, 1981; Harris, 1990). The results of this study are consistent with Harris argument that problems of nutrient deficiency and toxic residues in soils could become widespread at higher levels of fertilizer application in the long run.

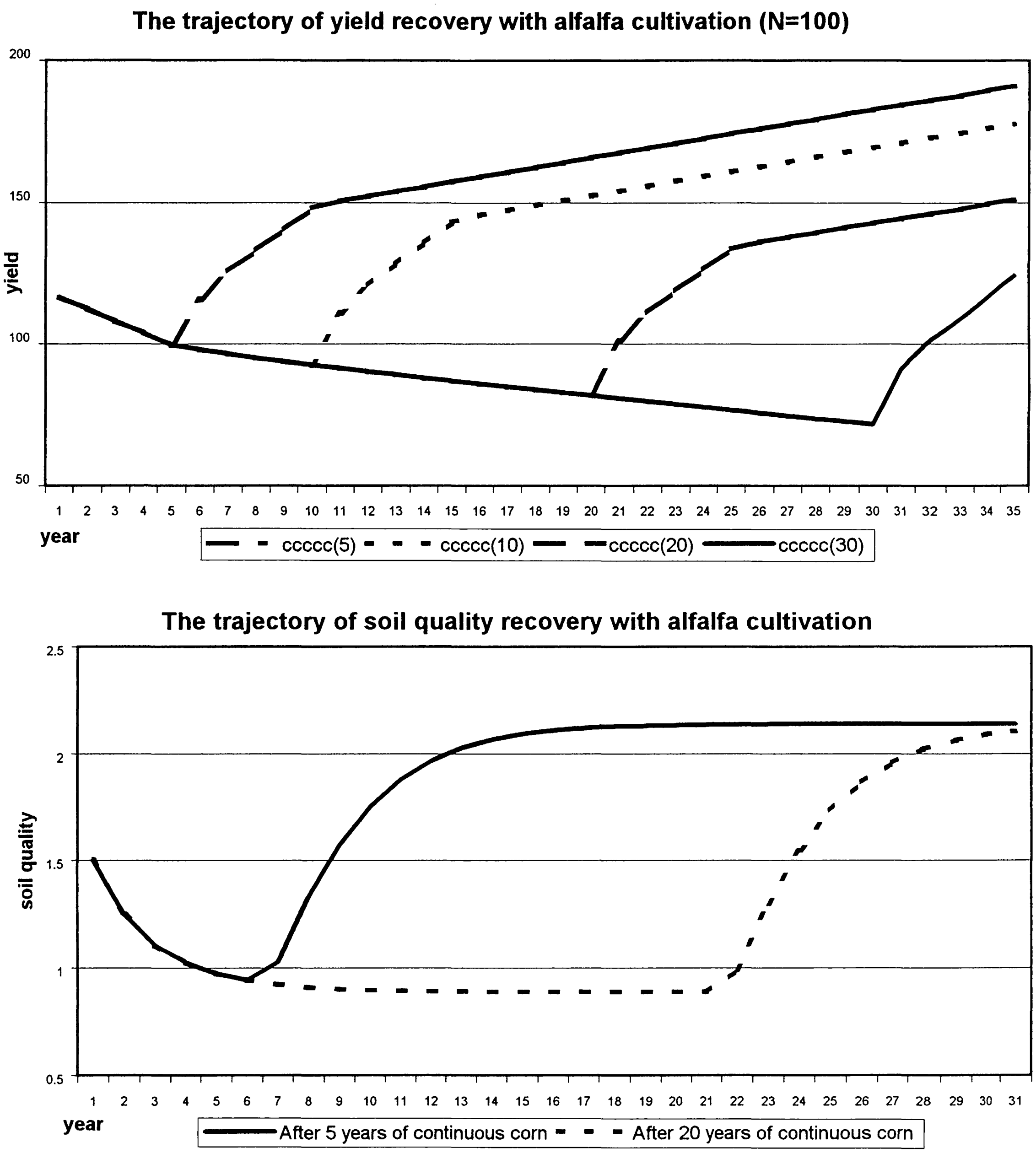


Fig. 6. The trajectories of yield and soil quality recovery through the use of alfalfa.

estimated value of $\alpha$ in the dynamic structural estimation, which provides the basis for a rapid decline and then flat trajectory, compared to the less restrictive RCM functional form which provides a more intuitive depiction of steadily declining yields under continuous corn that take progressively longer periods to regenerate. However, both sets of results demonstrate that the ability to draw inferences about soil quality and yield recovery times could constitute important economic information.

### 5.2. Other economic implications

The potential value of estimates of soil quality effects and recovery times is clear when designing and analyzing agricultural policies. First, it is evident that the economic optimality of rotations with N-fixing crops depends greatly on the returns to such crops. In mixed farming systems with significant livestock components, typical returns to alfalfa or soybeans may come close to matching those for corn. This is the case, e.g., in large areas of the US Midwest. Other farming systems have much smaller markets for green fodder or other products of legume crops, with the result that relative returns to these crops are much lower. This appears to be the case in many tropical agricultural systems, where the production of grains for consumption by humans and penned livestock is more important. If soil quality conservation is a policy goal, there may be sound economic arguments for subsidies on rotations that introduce lower-value, N-fixing crops to the production cycle. For example, soil quality conservation is an explicit goal of the US Conservation Reserve Program (CRP), in which participating farmers receive payments in return for taking land out of intensive cultivation, but whether the specific policies are appropriate depends on the underlying soil dynamics (Hertel and Preckel, 1988). Information from the application of our model to appropriate data could be important as an aid to the design of similar policies in other settings.

Information on soil quality dynamics is also important to ex post policy assessment. In many developing countries, e.g., private returns to corn, rice and wheat are enhanced by import-restricting policies aimed at promoting national self-sufficiency in staple cereals (Krueger et al., 1988). Several recent studies of such countries have sounded warnings about the implications of long-term declines in the quality of farmland used for intensive and continuous cereal cultivation (Byerlee, 1994; Cassman and Pingali, 1995). Failure to take such trends into account imparts a downward bias to assessments of the net social costs of food self-sufficiency programs (Coxhead, 1997). On the other hand, self-sufficiency programs could conceivably be implemented at lower social cost if they were able to make use of information about soil quality recovery rates. The parsimony of our methodology provides a way of approaching these long-term policy problems in countries where data are scarce.

Finally, although asymmetric information about land quality may not be a major impediment to private land market operation in wealthier economies, the same can by no means be said of developing countries. In such countries, lack of reliable information on recovery paths of soil quality could give rise to socially inefficient land use choices and land market performance (Kim and Chavas, 1999), with associated welfare costs. There is a strong economic case for using developing country crop trials data, e.g., from the international agricultural research centers, to examine long run soil quality dynamics in the way outlined in this paper. These efforts could potentially assist land-market participants in assessing the dynamics of soil quality and hence the underlying value of land based on its previous use.

More generally, for collaborative teams that might bring economists together with natural scientists to study the dynamics of soil quality under alternate management practices, our methodology provides a way of recovering the central state variable, and could thus be used in a wide variety of dynamic models of farmer behavior concerning land use and soil conservation investments. Such collaborative efforts might also give rise to a more explicit effort to incorporate phonological restrictions (as in the EPIC model) into the kind of dynamic econometric framework developed above. This could enrich both the richness of our understanding of the underlying dynamic processes of soil quality evolution and the statistical reliability of those more elaborate modeling approaches. The eventual social contribution of such collaborative undertakings could be quite great, as models of soil productivity dynamics are likely to be critical to policy analyses concerning long-term food production potential and environmental remediation for decades to come.

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