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Valuing Supporting Soil Ecosystem Services in Agriculture: a Natural Capital Approach

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ABSTRACT

Soil biodiversity through its delivery of ecosystem functions and attendant supporting ecosystem services—benefits soil organisms generate for farmers—underpins agricultural production. Yet lack of practical methods to value the long-term effects of current farming practices results, inevitably, in short-sighted management decisions. We present a method for valuing changes in supporting soil ecosystem services and associated soil natural capital—the value of the stock of soil organisms—in agriculture, based on resultant changes in future farm income streams. We assume that a *relative* change in soil organic carbon (SOC) concentration is correlated with changes in soil biodiversity and the generation of supporting ecosystem services. To quantify the effects of changes in supporting services on agricultural productivity, we fitted production functions to data from long-term field experiments in Europe and the USA. The different agricultural treatments at each site resulted in significant changes in SOC concentrations over time. Declines in associated services are shown to reduce both maximum yield and fertilizer-use efficiency in the future. The average depreciation of soil natural capital, for a 1% relative reduction in SOC concentration, was 144 € ha^{-1} (SD 47 € ha^{-1}) when discounting future values to their current value at 3%; the variation was explained by site specific factors and the current SOC concentration. Moreover, the results show that soil ecosystem services cannot be fully replaced by purchased inputs, they are imperfect substitutes. We anticipate our results will both encourage and make it possible to include the value of soil natural capital in decisions.

Keywords: soil organic carbon; economic valuation; sustainable agriculture; ecological intensification; land use

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The global challenge facing agriculture is meeting future demand for food and bioenergy, while simultaneously reducing its contribution to environmental degradation and climate change (Cassman et al., 2003; Foley et al., 2011). Hitherto increases in yields have been accompanied by prodigious increases in the use of pesticides and mineral fertilizers (Matson et al., 1997). Further increases might be possible with this approach alone (Mueller et al., 2012), but in the long-run environmental damage will impose costs through losses of *ecosystem services*[1] (Tilman et al., 2001; Carvalheiro et al., 2011). Alternatively, it is claimed that more environmentally friendly and resource-efficient agriculture could be achieved by better utilizing supporting ecosystem services in agriculture (Cassman, 1999; Bommarco et al., 2013).

Soil biodiversity underpins agricultural productivity through interactions that generate functions and ultimately supporting ecosystem services such as: i) decomposition of organic material and production of soil organic matter, ii) nutrient cycling and mineralization, iii) biological control of agricultural pests and diseases, and iv) soil structure formation, e.g., water infiltration and holding capacity (Barrios, 2007; Wall et al., 2012). Soil organisms also generate regulating services such as degradation of pollutants to maintain clean ground water, and regulating the fixation and release of CO_2 and other greenhouse gases, e.g. CH_4, and N_2O (Andrén et al., 2004; Lal, 2010; de Vries et al., 2013).

To the extent that soil biodiversity benefits farmers and these benefits or supporting ecosystem *services* are recurring then soil biodiversity is, from an economic perspective, equivalent to other assets (e.g., breeding livestock), and should be valued and managed from a long-term perspective (Barbier, 2007). In this sense soil biodiversity is the soils' *natural*

[1] We follow the Millennium Ecosystem Assessment nomenclature (MEA 2005) by distinguishing between supporting, regulating and provisioning ecosystem services to categorize the benefits humans receive from ecosystems. In the context of this article, supporting services associated with soil processes provide farmers with indirect benefits through their contribution to crop production (a provisioning service).

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capital that is part of total soil capital; which we consider in the abstract economic sense as the aggregate capacity of an arable soil to produce crops sustainably.

Our economic perspective is not necessarily inconsistent with approaches that focus on describing and quantifying, e.g., the component parts of soil capital (Robinson et al., 2009; Dominati et al., 2010), soil quality (Nortcliff, 2002) or soil health (Doran, 2002); they are presumably complimentary, providing different kinds of information for decision support at different scales and for different types of questions. To be useful for farm or societal-level decision-making, soil natural capital needs to be conceived and measured at a sufficient level of abstraction, for answering questions such as what is the optimal or desirable stock of soil natural capital.

To inform decision makers of the importance of ecosystem services, the *Natural Capital* framework has emerged for internalizing their value in decision-making (Sukhdev et al., 2010; Kareiva et al., 2011). A growing literature on the identification and valuation of ecosystem services is also evolving (Fisher et al., 2009; de Groot et al., 2012). Despite recognition that supporting soil ecosystem services are essential to agricultural production, their economic value has not been well understood or quantified (Robinson et al., 2009; Dominati et al., 2010). Economic valuation of physical degradation of soils has been applied to erosion (e.g., Burt, 1981; Smith and Shaykewich, 1990; Goetz, 1997), but a general approach to assessing the economic impacts of changes in soil natural capital is lacking, though it is needed (e.g., Van-Camp et al., 2004).

We present a method that aims to value, in monetary terms, the contribution of supporting soil ecosystem services and associated soil natural capital to agricultural productivity. Valuation requires in a first step estimating production functions (yield response functions) that quantify the effects of changes in flows of supporting ecosystem services (via an indicator) on future attainable yields and input-use efficiency. In the second step the

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marginal value (or "marginal user cost") of soil natural capital is inferred from resulting changes in future farm income streams, which is equivalent to the depreciation in the stock of soil natural capital resulting from a small reduction in the stock. In a final step we show how the value can differ depending on the extent of the decision-maker's concern for the future, i.e., an individual farmer aiming to maximize their current income or from a societal perspective that includes future generations.

To value soil natural capital an indicator of flows of supporting soil ecosystem services is needed, as measuring changes in the biodiversity that mediates services is far from straight-forward, due to the complexity of soil food webs and knowledge gaps regarding the specific functions of the multitudes of different organisms inhabiting arable soils (Bardgett et al., 2005; de Vries et al., 2013). Soil organic carbon (SOC) is here used as a proxy for soil biodiversity as it is correlated with soil biodiversity and food webs (de Ruiter et al., 2005; Tsiafouli et al., 2015), as well as a number of supporting ecosystem services (Endale et al., 2010; Williams and Hedlund, 2014). Furthermore, SOC is generally considered a major factor in a soil's overall health and agricultural productivity (Johnston et al., 2009).

Agriculture can deplete soil biodiversity and SOC as a result of intensive soil tillage, inadequate crop rotations, insufficient organic inputs and erosion (Paul et al., 1997; Pan et al., 2009; Luo et al., 2010; Palm et al., 2014). Consequently, conventional management of soils can result in annual losses of organic matter that seem tiny, commonly a 0.2 to 1% relative loss of SOC per year, but in the long term result in considerable depletion of SOC stocks (Davidson and Ackerman, 1993; Riley and Bakkegard, 2006; Sanderman and Baldock, 2010; Meersmans et al., 2011), and with this reduced capacity to generate supporting ecosystem services (Powlson et al., 2011).

Conversely maintaining higher levels of SOC requires increasing organic inputs to the soil through, e.g.: application of stable manure, sewage sludge, compost, etc., and crop

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residues such as straw (Persson and Kirchmann, 1994; Blair et al., 2006; Liu et al., 2014), or using cover crops and legumes (Thomsen and Christensen, 2004). Moreover root-derived carbon is considered a main driver of SOC sequestration (Kätterer et al., 2011). This can be improved through extending plant cover such as having a perennial plant in the crop rotation (Christensen et al., 2009; Luo et al., 2010), or by reducing the intensity of tillage (Wang et al., 2011; Clay et al., 2012). Finally increased fertilizer rates can slow down the rate of SOC decay if it results in larger volumes of harvest residues being returned to the soil or more roots (Alvarez, 2005). Accordingly SOC concentration is not easily manipulated in the short-run, in contrast to say plant available N (via fertilizer application) or water (via irrigation).

Thus SOC is not only a component of soil capital, but a relative change in SOC is, potentially, a practical indicator of changes in flows of supporting ecosystem services and associated soil natural capital. It has not previously been used in economic valuation as a general indicator of supporting ecosystem services, but for other intentions (e.g., Belcher et al., 2003; Kuhlman et al., 2010). Here we present an approach that uses long-term experimental data to *estimate* the effects of changes in supporting ecosystem services on soil productivity based on changes in SOC concentration, and thereafter values soil natural capital on the margin using economic theory.

MATERIALS AND METHODS

Inferring the value of soil natural capital

Our approach to valuing supporting ecosystem services follows from Envelope Theorems in mathematics that describe how the optimal value of the decision-maker's objective function (in a parameterized optimization problem) changes as one of the parameters changes (e.g., Simon and Blume, 1994, p. 453). By analyzing the effect of a small change in soil natural capital on maximal future farm income streams we can infer its value to the farmer (its marginal user cost) based on economic theory for valuing unpriced but scarce inputs.

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Fundamentally, our valuation is based on a crop production function that quantifies changes in yield and the minimum fertilizer input needed to achieve a particular yield for different stocks of soil natural capital. A crop production function is a parametric function that describes what is possible to produce with different combinations of inputs (these can be either natural or man-made or both). We estimate production functions using balanced panel data sets on wheat yield, fertilizer input and SOC concentration generated from long-term agricultural field experiments in four representative arable cropping regions in Europe and North America. The advantage of these experiments is that applications of fertilizer (increasing rates applied to different experimental plots) and other soil management practices are controlled (Rasmussen et al., 1998), thereby avoiding problems often found in economic data, e.g., multi-collinearity between independent variables in farmer surveys.

To value changes in soil natural capital the best estimated production function for each site was integrated with an economic optimization model that describes the farmers' decision problem with a suitable behavioral goal (i.e., income maximization). We subsequently used observed market prices (objective values) of the provisioning ecosystem service (wheat) and man-made inputs (mineral fertilizer) to infer the contribution of supporting ecosystem services to annual farm income streams; and subsequently value changes in soil natural capital in present value calculations (for different ranges of the necessarily subjective discount rate). We assume the farmer optimizes fertilizer application to maximize gross farm profit (income) given the current state of soil natural capital, since dynamic optimization is beyond the scope of this paper.

Overview of long-term field experiments

We begin by describing the four long-term experiments before presenting the theoretical production functions and economic valuation models. For selection of the experimental treatments it was important that soil management and crop rotations at each site have

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developed different concentrations of SOC over time. Measurements of SOC were taken at regular intervals (1–10 years) over the course of the experiments but not necessarily annually since concentrations change slowly. For years when measurements of SOC were not taken we estimated the values by fitting an exponential function to the data points. Table 1 summarizes the data for each region.

[Insert Table 1]

Swedish Long Term Fertility Experiments

The Scanian experiments consist of five proximate sites in the south of Sweden that have been running continuously since 1957 (Carlgren and Mattsson, 2001). The climate is cold-temperate at all sites (1=Ekebo, 2=Fjärdingslöv, 3=Orup, 4=Södra Ugglarp and 5=Örja) with a mean annual temperature of 7.64°C and annual precipitation of 655 mm across the sites. The data from the five sites was combined to create a single database for Scania as the treatments at each site are identical and they are subjected to similar weather. To control for site specific factors such as differences in soil properties other than SOC concentration, we estimated the yield functions for this region using a fixed-effects model. Each sub-site has two parallel crop rotations with four different fertilizer application rates per rotation. For winter wheat the application rates are: 0, 50, 100 and 150 kg N ha^{-1}, and replacement of phosphorous (P) and potassium (K) according to amounts removed with harvest. Rotation I mimics conditions on farms with livestock and hence includes application of farm yard manure (FYM) at a rate of 20 tons of solid manure ha^{-1} every fourth year, a grass fodder crop and removal of harvest residues. The plant available N in FYM (assumed to be 20%) is included in the estimation of the production functions. The order of crops in the rotation is: spring barley, grass ley, winter wheat and sugar beet. Rotation II mimics specialized arable cropping without livestock. Hence there is no addition of FYM and harvest residues are incorporated in

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the soil after harvest. The order of crops in the rotation is: spring barley, spring rapeseed, winter wheat and sugar beet. Percent SOC was measured every fourth year.

Static Fertilization Experiment Bad Lauchstädt, Germany

The *Bad Lauchstädt Experiment* started in 1902 to investigate the effects of mineral and organic fertilizers on yields and crop quality (Merbach and Schulz, 2012). Maintenance of soil fertility has been an additional goal of the experiment. The climate is cool-temperate with a mean annual temperature of 8.78°C and annual precipitation of 484 mm. Four different crops have been grown in rotation since the experiment began: sugar beet, spring barley, potatoes, and winter wheat. The site is divided into three fields that have received different organic fertilizer treatments. FYM has never been applied to the first field, but has been applied to the second and third fields at 20 (FYM I) and 30 (FYM II) t ha^{-1} bi-annually (after the harvest of cereals). Each field has been divided into six plots which have received varying amounts of mineral fertilizer; ranging from no mineral fertilizer being added to the following combinations of nutrients: PK, N, NK, NP or NPK. Each plot is further divided into eight sections. While treatments in sections 1, 4, 5 and 8 have been changed over the years in response to new research questions, sections 2, 3, 6 and 7 have remained under the same treatments since the start. The amounts of mineral N, P and K have fluctuated over the course of the experiment, as well as among the different crops. N application to winter wheat has ranged between zero for the control and annually fluctuating rates of 40–100 kg N ha^{-1} yr^{-1} for the mineral fertilized plots. Data on yields of winter wheat and concentrations of SOC from 1956–2010 were used to estimate the production functions for this site. SOC was measured in the years 1956, 1966, 1969, 1971, 1973 (which corresponds to the years of planting of winter wheat) and annually since 1976. Hence only SOC data for a single year, 1960, was missing for this site.

Askov Experiment on Straw Incorporation, Denmark

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The relevant Askov experiment started in 1981 to study the effect of different straw application rates on SOC (Thomsen, 1995). The climate is cold-temperate with a mean annual temperature of 7.7°C and annual precipitation of 862 mm. Spring barley was grown in the experiment in each of the years 1981–99. At harvest, barley straw was either removed or applied at rates of 4, 8 and 12 t ha^{-1} depending on the plot. Standard N application was 100–125 kg N ha^{-1} yr^{-1} in spring. The yield data used to estimate the production functions for this site was obtained in 2000, 2001 and 2002 when winter wheat sown in September of the previous year was used to test the residual value of the repeated straw incorporation on SOC concentration (Thomsen and Christensen, 2004). Each of the previous treatments was divided into four subplots receiving 0, 60, 120 or 180 kg N ha^{-1} in spring. The plots were supplied with the same N rate each year and received in addition 17 kg P ha^{-1} and 88 kg K ha^{-1}. SOC was measured in December 1999 and again in October 2002 (i.e., at the start and end of the wheat experiments).

Pendleton Residue Management Long-term Experiment, Oregon, USA

The Pendleton experiment started in 1931 and is representative of cropping systems in the Pacific Northwest intermountain cereal region and has a mean annual temperature of 10°C and annual precipitation of 419 mm (Rasmussen and Smiley, 1997; Machado, 2011). The two-year rotation studied is winter wheat–fallow with conventional (moldboard) tillage. The experiment consists of nine treatments with various forms of stubble management and fertilizer application (both organic and inorganic). The current treatments are: 0) no burning and zero N, 2) spring burning and 45 kg N ha^{-1}, 3) spring burning and 90 kg N ha^{-1}, 4) no burning and 45 kg N ha^{-1}, 5) no burning and 90 kg N ha^{-1}, 6) fall burning and no N, 7) spring burning and no N, 8) no burning and 22.4 t ha^{-1} FYM applied every other year to the fallow, and 9) no burning and 2.24 t ha^{-1} pea vines applied every other year to the fallow. SOC concentration has been measured at intervals of approximately 10 years starting in 1931.

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Theoretical production functions

We compared three well-known forms of crop production functions for modeling the joint effects of nitrogen fertilizer (both organic and mineral sources) and SOC concentration on the yield of winter wheat: the quadratic, Mitscherlich-Baule (M-B) and quadratic-plus-plateau functions (Cerrato and Blackmer, 1990; Frank et al., 1990). We also tried other forms of functions (e.g. linear and cubic) but found them inferior to the three functions presented here.

The quadratic function in two variables is specified as

$$Y(C,N) = a_1 + a_2 N + a_3 N^2 + a_4 C + a_5 C^2 + a_6 NC \qquad (1)$$

where Y is yield (kg ha^{-1}), and N is input of plant available nitrogen (kg N ha^{-1}) from both mineral and organic sources (e.g., farm yard manure, FYM), and C is SOC concentration (g kg^{-1}) in the top layers of the soil.

The two-variable M-B function is specified as

$$Y(C,N) = b_1[1-\exp(-b_2(b_3+N))][1-\exp(-b_4(b_5+C))] \qquad (2)$$

with maximum (asymptotic) yield given by b_1 which occurs when both $N, C \to \infty$.

The two-variable quadratic-plus-plateau function is specified as

$$\begin{aligned}
Y(C,N) &= a_1 + a_2 N + a_3 N^2 + a_4 C + a_5 C^2 + a_6 NC && \text{for } N \le \bar{N} \text{ and } C \le \bar{C},\\
Y(C,N) &= a_1 + a_2 \bar{N} + a_3 \bar{N}^2 + a_4 C + a_5 C^2 + a_6 \bar{N}C && \text{for } N \ge \bar{N} \text{ and } C \le \bar{C},\\
Y(C,N) &= a_1 + a_2 N + a_3 N^2 + a_4 \bar{C} + a_5 \bar{C}^2 + a_6 N\bar{C} && \text{for } N \le \bar{N} \text{ and } C \ge \bar{C},\\
Y(C,N) &= a_1 + a_2 \bar{N} + a_3 \bar{N}^2 + a_4 \bar{C} + a_5 \bar{C}^2 + a_6 \bar{N}\bar{C} && \text{for } N > \bar{N} \text{ and } C > \bar{C}
\end{aligned} \qquad (3)$$

where $\bar{Y} = a_1 + a_2 \bar{N} + a_3 \bar{N}^2 + a_4 \bar{C} + a_5 \bar{C}^2 + a_6 \bar{N}\bar{C}$ is plateau (maximum) yield, and $\bar{N}$ and $\bar{C}$ are the critical levels of C and N.

Estimation procedures

To estimate the production functions we used data on wheat yields resulting from a range of fertilizer application rates (primarily N kg ha^{-1}) over a range of SOC concentrations (g kg^{-1}). Independent functions were estimated from the dataset for each site. The variables in Eqs. (1–

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3) are related to the data for each site as follows: the dependent variable Y_t is observed yield in year $t \in V$ where $V = \{1931,...,2007\}$. The independent variable N_t is plant-available nitrogen input in year t, and C_t is measured SOC (g kg^{-1})—or interpolated SOC for years with missing data—in year t. Each experimental treatment is defined by a set of management practices (e.g., tillage regime, crop rotation, etc.) and fertilizer regime. The indirect effects of management on yield (i.e., carry-over effects to subsequent years) are captured via changes in SOC (C_t) since this is a measure of supporting ecosystem services, and the direct effect by the chosen nutrient application rate (N_t).

To account for year effects in the data, such as stochastic weather events and technological developments affecting yields, we estimated year-effect parameters for each site, denoted h_t (noting t is the year of a particular observation), by using the indicator function $I_j(t)$ that returns 0 if $j \neq t$ and 1 if $j = t$ where $j \in V$. Further, because Scania comprises five sub-sites we considered the potential sub-site specific or fixed effect (brought about by potential differences in, e.g., physical soil properties), denoted l_n using the indicator function $I_m(n)$ that returns 0 if $m \neq n$ and 1 if $m = n$ where $m \in (1,...,5)$ and $n \in (1,...,5)$ is the location of the observation. Therefore, each observation is characterized by a particular year by adding the term $\sum_{j \in V} h_t I_j(t)$ to each of the theoretical models to be estimated for each region, and additionally for Scania the term $\sum_{m \in U} l_n I_m(n)$ to recognize the sub-site specific effect.

Production functions were estimated independently for the four regions because of uncontrollable factors, particularly climate, that would be expected to influence crop response to fertilizer and changes in SOC. The quadratic models were estimated using the maximum likelihood approach in EViews. The M-B models were estimated using the SPSS nonlinear regression package and the Levenberg-Marquardt method. The quadratic-plus-plateau models

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were estimated using the Gauss-Newton method as implemented in the REG and NLIN procedures of SAS.

Model selection procedure

We designed a set of plausible models for each functional form based on prior information about the importance of the parameters, which resulted in a suite of eight different variations of the theoretical quadratic and quadratic-plus-plateau functions, and nine variations of the M-B function (Supplemental Table S1). In total 25 functions were estimated for each site and the best model was selected based on the following selection procedure. For all models we obtained the log-likelihood and AIC values: AIC=2*k*-2ln(*L*) where *k* is the number of parameters in the statistical model, and *L* is the maximized value of the likelihood function for the estimated model. The model with the minimum AIC is the best fitting model according to this criterion. A small difference in AIC (i.e., less than 2) is generally considered as no difference between the models (Bolker, 2008). The function meeting this criterion was selected as the best fitting model for that functional form. In cases where a single model could not be selected based on the AIC, the AIC Weight, which represents the relative likelihood of a model, was used to identify the best model.

Economic valuation model

To value changes in soil natural capital we needed first to consider the influence of changes in SOC on yield and fertilizer use, and second the concomitant impact on maximum annual profits in the future. This was done by integrating the production functions with an economic model of farmer behavior (for a full mathematical exposition of the approach adopted see, e.g., McConnell and Bockstael (2005).

Contribution of supporting ecosystem services to productivity

In the valuation we assume that farmers aim to maximize profit by optimizing fertilizer input *N* given the soil's current stock of natural capital (i.e., SOC concentration), C^0. Let $Y(C,N)$

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represent the quadratic yield response function specified in Eq. (1) because this is the function selected in the empirical valuation, p be the unit price of wheat and w the unit price of fertilizer with other costs assumed to be fixed per unit area (since these are not in focus here). The farmers' optimization problem, given $C=C^0$, is formulated as

$$\pi_{\max}\left(N \mid C^0\right) = \max_N pY\left(N \mid C^0\right) - wN, \tag{4}$$

and since the yield function is concave the objective function is also concave; hence, the optimality condition for maximum profit is

$$\frac{\partial \pi}{\partial N} = p\left(a_2 + 2a_3 N + a_6 C^0\right) - w = 0. \tag{5}$$

It follows that the solution for optimal N input, N^*, given the current SOC concentration, C^0, is

$$N^*\left(C^0\right) = \frac{w - p\left(a_2 + a_6 C^0\right)}{2a_3 p}. \tag{6}$$

Let us now assume that the SOC concentration to be carried forward to future years, declines by a small amount ΔC^0 to some new level $C^1 = C^0 - \Delta C^0$. The consequent change in optimal fertilizer input in the future brought about by this marginal reduction in SOC is

$$\Delta N = N^*\left(C^1\right) - N^*\left(C^0\right), \tag{7}$$

and the associated change in future optimal yield is

$$\Delta Y = Y\left(N^*\left(C^1\right) \mid C^1\right) - Y\left(N^*\left(C^0\right) \mid C^0\right). \tag{8}$$

Fertilizer use efficiency is defined as the yield per unit of applied fertilizer. Following from Eqs. (7) and (8) the change in fertilizer use efficiency brought about by the change in SOC is $\Delta Y / \Delta N$ (kg wheat/kg N).

Change in maximum annual profit

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Maximum annual profit, π_{max}, is represented by the value function which is found by substituting the solution for optimal fertilizer input Eq. (6) given *C,* into the objective function, Eq. (4), which gives

$$\pi_{\max}\left(N^* \mid C\right) = p\left(a_1 + a_2N^* - a_3\left(N^*\right)^2 + a_4C - a_5C^2 + a_6CN^*\right) - wN^* . \tag{9}$$

Consequently, the change in future maximum annual profit brought about by the imposed change in SOC is

$$\Delta\pi = \pi\left(N^*\left(C^1\right) \mid C^1\right) - \pi\left(N^*\left(C^0\right) \mid C^0\right) \tag{10}$$

which follows from Envelope Theorems.

The marginal value of soil natural capital

The marginal economic value of soil natural capital equals the change in the present value of the future profit stream due to a change in the current stock (e.g., Barbier, 2007). The present value (PV) of the cumulative change in future profits implied by Eq. (10) is (e.g., Polasky et al., 2008):

$$PV = \Delta\pi\sum_{i=0}^{\infty}\frac{1}{\left(1+\delta\right)^i} = \frac{\Delta\pi\left(1+\delta\right)}{\delta} \tag{11}$$

where *i* is the year in the future and δ is the discount rate, which is an assumption by economists whereby what happens in *i* years from now is valued less by a factor $(1+\delta)^{-1}$ per year.

Procedure for interpolating missing SOC data

Prior to estimating the production functions for each site it was necessary to interpolate any missing SOC data for the intermittent years when measurements were not taken. After testing various functional forms, an exponential function was found to best represent the 67 datasets resulting from the different treatments and any changes in treatments across all sites (40

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functions for Scania from 5 sub-sites with 8 treatments each, 6 for Bad Lauchstädt, 4 for Askov, and 17 for Pendleton):

$$C(t) = C_S \exp(rt), \tag{12}$$

where the dependent variable $C(t)$ is measured SOC (g C kg^{-1}) in year t, C_s is measured SOC at the start of the experiment, and r (the parameter to be estimated) is the annual rate of change in SOC brought about by a particular treatment. This choice of functional form is also supported by Sanderman et al. (2010) who have studied changes in SOC with data from 13 long-term field experiments around Australia. Missing values were subsequently calculated from the treatment-specific equations for each site, i.e., Eq. (12), for the appropriate year.

Modelling a marginal change in SOC

Based on the experimental data a marginal change in SOC for the ensuing valuation was computed as a relative rather than an absolute change. According to Eq. (12) the current SOC concentration is a consequence of its initial concentration, C_s, and its annual rate of change, r, as dictated by the choice of management practices. Consequently, SOC in the following year will change relative to the current concentration by a factor exp(r). Therefore, since land that has been arable for some time will affect SOC exponentially by small amounts from one year to the next, we modelled a marginal change in SOC as a 1% relative change from its current level to predict future impacts on yield and fertilizer use efficiency (a change which is small enough, i.e., marginal, to be consistent with the annual decision period that characterizes arable cropping). The concomitant effect on maximum profit was subsequently determined by combining the selected production function for each site with the objective function, Eq. (4).

Consequently a marginal change in soil natural capital is modeled as: $\Delta C^0 = 0.01 \times C$ where C (g kg^{-1}) is the assumed *current* SOC concentration in the forthcoming valuations (to be defined as either **LOW, TODAY** or **HIGH**). The **TODAY** concentration was set equal to the ending SOC concentration for the experimental treatment that is most representative of

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farming practices in each region: Scania 18.7 g kg^{-1} (average of Treatment IIB3 over the five sub-sites); Bad Lauchstädt 18.1 g kg^{-1} (Treatment 13); Askov 13.4 g kg^{-1} (average of Treatments 1b and 1c); Pendleton 11.2 g kg^{-1} (Treatment 5 in 1986). We subsequently tested the sensitivity of the valuation results to the current SOC concentration by evaluating hypothetically low and high SOC concentrations where we assumed **LOW** is 20% lower and **HIGH** is 20% higher than the **TODAY** level.

RESULTS

Estimated rates of SOC change

The different agricultural treatments at each site resulted, generally, in significant differences in annual rates of SOC change and thus final SOC concentrations (Table 2). Mineral fertilizer alone was generally not sufficient to stop SOC losses, but higher application rates slowed the rate of loss. Including a grass ley in the rotation with some FYM application (Scania IB0–3) or pea vine (Pendleton 9) improved SOC retention even further. Relatively large inputs of FYM could boost or maintain SOC (Bad Lauchsädt 1–12, Pendelton 8). The Askov experiment shows the importance of returning harvest residues to the soil. By adding straw over a 20 year period, large increases in SOC were achieved; the more straw the greater the increase (SOC Start).However removing straw in subsequent years (the period we studied) caused rapidly declining SOC (Askov 1b-d). The resultant variations in SOC concentrations between treatments at each site are next utilized to estimate the implications for agricultural productivity using production functions.

[Insert Table 2]

Quantifying soil supporting ecosystem services with production functions

All models of the production function for each site predicted similar maximum yield and similar minimum fertilizer input to achieve this yield for a given SOC concentration

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(Supplemental Fig. S1). The statistically best fitted model was the quadratic model for Scania, Bad Lauchstädt and Pendleton, and the M-B model for Askov (Table 3) according to the highest AIC weight across all models (Supplemental Table S3). However, since the AIC weight for the quadratic model for Askov is not much lower and both models provide similar fits to the data either can be chosen.

[Insert Table 3]

The selected production functions show that supporting ecosystem services, as indicated by changes in SOC concentration, have a significant positive effect on yield and fertilizer use efficiency. First, the maximum attainable yield increases with SOC concentration, e.g., Scania's maximum yield changes by 3237 kg ha^{-1} with a SOC shift from 7.9 to 19.0 g C kg^{-1} (Fig. 1). Second, less fertilizer is needed to produce a unit of wheat with higher SOC. For Scania the maximum yield at 19.0 g C kg^{-1} is 7917 kg ha^{-1} and requires 135 kg N ha^{-1}, whereas at 7.9 g C kg^{-1} the maximum yield is 4680 kg ha^{-1} and requires 150 kg N ha^{-1}, thus causing fertilizer use efficiency to fall from 59 to 31 kg wheat/kg N (ha^{-1}).

[Insert Fig. 1]

The reduction in fertilizer use efficiency implies that mineral fertilizer is not a perfect substitute for supporting soil ecosystem services: the greater the curvature of an isoquant—the combinations of fertilizer N and SOC concentration that produce a particular yield—the greater the amount of fertilizer that is needed to substitute for reduced supporting services to maintain yield (Fig. 2). If fertilizer and SOC were perfect substitutes then the isoquants would be straight lines. Thus, the highest attainable yields are only possible in combination with relatively high levels of SOC (i.e., soil natural capital).

[Insert Fig. 2]

Finally, it is the relative change in SOC at a particular site that is the key to the ensuing marginal valuation of soil natural capital. The actual yield generated at a particular site is

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affected by other properties of the soil such as clay content, pH, etc. and local climate. A relative change in SOC concentration can in our approach act as a proxy for changes in flows of ecosystem services generated by soil organisms at each site (all other things equal). For instance the maximum yield at 15.0 g C kg^{-1} ranges from 7011 to 8273 kg ha^{-1} across the three European sites. Moreover the marginal productivity of SOC is decreasing, meaning that increasingly higher SOC concentration will generate smaller and smaller increments in yield, and ultimately retarding it (which occurs for Scania when SOC > 29.4 g kg^{-1}). Thus for soils with high SOC (e.g., peat soils) the marginal value of soil natural capital (as indicated by SOC concentration) with respect to agricultural productivity may be zero or negative, even though the value of regulating functions may be high (Raudsepp-Hearne et al., 2010).

Impact on future profit streams

As we model changes in SOC as relative changes, the absolute change in SOC concentration will vary with the current concentration (Fig. 3a): the higher the current concentration at a site (**LOW**, **TODAY** or **HIGH**) the larger the absolute change in SOC. The marginal productivity of SOC over the evaluated SOC range at each site is decreasing for Scania and Askov, and increasing for Bad Lauchstädt and Pendleton (Fig. 3b). Generally, fertilizer productivity (Δyield/ΔN) is increasing with SOC (Fig. 3c), however, for Askov a downward trend is discernible because both the quadratic SOC term and N×SOC-interaction term were not significant for this site (Table 3); recall the evaluated SOC range for Askov was quite narrow. Because the overriding effect of a change in SOC is on yield, the effect on maximum profit is dominated by the change in yield: consequently, the marginal profit is decreasing for Scania and Askov, and increasing for Bad Lauchstädt and Pendleton over the evaluated ranges of SOC (Fig. 3d). For Pendleton the marginal productivity of SOC for the **HIGH** scenario is very high, and consequently the marginal profit is very high.

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In summary, the sizes of the effects caused by a marginal change in SOC were dependent on the current state of SOC and the site. The predicted changes in maximum annual profit are also small compared to total profit for each site and SOC assumption (< 1%). Nevertheless, because the change in maximum profit occurs every year in the future, it will affect future profit streams and hence imply a change in the value of the underlying stock of soil natural capital.

[Insert Fig. 3]

Marginal value of soil natural capital

The present value of the change in future profits brought about by a change in soil natural capital (SOC) is calculated according to Eq. (11) for different values of the discount rate δ (i.e., 1.4–28%). The price of winter wheat is assumed to be €0.15 kg^{-1} and that of nitrogen €1.10 kg^{-1} based on expected market prices in 2012 (AgriWise, 2012).

The range of the marginal value of soil natural capital at each site was affected strongly by the discount rates applied (Fig. 4): where 1.4–3% (Stern, 2006) can be regarded as a standard interval for public investments and 3–7% is more reflective of affluent farmers, while higher discount rates are likely among farmers who treat their land as just another investment or cannot afford the short-term costs of soil conservation measures.

When future profits are discounted at 1.4%, a 1% relative reduction in SOC depreciates the value of soil natural capital by, on average, €263 ha^{-1} (SD €194 ha^{-1}), whereas an extreme rate of 28% implies a loss of only €17 ha^{-1} (SD €12 ha^{-1}). Therefore, a small change in supporting ecosystem services is likely to have a substantial impact on the value of soil natural capital to society whereas for farmers (the soil managers) its marginal value will be more dependent on individual preferences over the future. Their respective valuations will also be influenced by local conditions (as indicated by the relatively large variation in marginal values between sites) and the current SOC concentration.

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[Insert Fig. 4]

SUMMARY AND DISCUSSION

We demonstrate that declines in supporting soil ecosystem services, as correlated with relative changes in soil organic carbon (SOC) concentration, reduce both future attainable yields and fertilizer-use efficiency. By quantifying these effects with empirical production functions we could infer the associated depreciation (or appreciation) of the stock of soil natural capital as a basis for informing long-term decision-making. Our results also show that supporting soil ecosystem services cannot be fully replaced by mineral fertilizers—they are imperfect substitutes—which is reason enough for careful conservation of soil biodiversity. We also show that the marginal value of soil natural capital will be sensitive to its current state (as indicated by SOC concentration), site characteristics and the extent of the decision-maker's concern for the future (as represented by the choice of discount rate).

Without an objective basis for the choice of the discount rate (Weitzman, 2007) the marginal valuation of soil natural capital at each site (Fig. 4) was presented as ranges. Accordingly the valuation of soil natural capital includes an objective part, the change in future income streams based on the production function, and a subjective part, the choice of discount rate. Sensitivity of the valuation to the choice of discount rate implies that farmers will likely conserve less soil natural capital than is socially desirable.

To quantify the potential impact of changes in supporting soil ecosystem services on agricultural productivity we chose a production function approach. An alternative approach to productivity analysis is data envelopment analysis (DEA), but its advantages are overshadowed by its limitations for our purposes (Jaenicke, 2000). Each of the chosen functional forms has though its advantages and disadvantages. Overall the quadratic function provided the best or equal-best model for all sites. Given that it is also the most general of the forms tested, and its modeled yields were reasonable in comparison to the observed ranges of

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yields (Supplemental Table S4) we based the economic valuation, for comparative purposes, on the best quadratic model for each site, a choice which is also supported by, e.g., Benbi and Chand (2007).

Others have attempted to value changes in SOC but not as a general indicator of flows of supporting ecosystem services (e.g., Belcher et al., 2003; Kuhlman et al., 2010). The obvious next step in our research will be to study the optimal management of soil natural capital over time, which requires a dynamic optimization framework (e.g., McConnell, 1983). Solving this problem was beyond the scope of this paper, but in principle the rational decision maker needs to weigh the immediate cost of adopting conservation practices (which is easily observable) against the present value of the future benefits of conservation, which are not easily observable, but are estimated here. Similar reasoning could be applied if the broader social benefits of conserving soil natural capital such as water purification and carbon sequestration were also considered; which is also future work. We also believe in the urgency of devoting research to valuing soil natural capital in an uncertain world and its potential effectiveness for managing agricultural risks (e.g., Cong et al., 2014).

Historically, advances in technology and relatively low energy prices have made soil resources per se of less consequence for agricultural production (Burt, 1981). However with recent surges in energy and other input prices, general concerns about the environmental sustainability of agriculture and the threats of climate change, there is reason to investigate the potential global benefits of optimizing soil natural capital in agriculture (Lal, 2010). This study may value small, relative changes in soil natural capital at the field level and from an agricultural perspective but it has global implications. Consider, for example, that around 25 million ha of wheat is cultivated in the EU annually (~220 million ha globally) using ~1.5 million tonnes of mineral N fertilizer (~17 million tonnes globally) (FAOSTAT, 2012). Based on the average effects for our EU sites (Fig. 3) a one-off, 1% relative reduction in SOC

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concentration across the EU's wheat fields would reduce annual output by ~740 thousand tonnes using the same amount of fertilizer or require an additional ~7300 tonnes of N fertilizer to maintain output ceteris paribus. This translates to depreciation of the value of the EU's soil natural capital by ~€9 billion (for a tiny, one-off reduction in SOC per ha), which can be compared to the negligible short-term (i.e., annual) cost to farmers of ~€5 ha^{-1} yr^{-1}.

Failure to recognize the value of soil biodiversity in production implies that the resource-use efficiency and sustainability of global agriculture could be undermined by 'a tyranny of small decisions' if the countless farmers managing the myriad fields across the planet and for indefinite future generations, are failing to consider the long-term economic value of supporting ecosystem services in their management decisions. This is not improbable because as we show the short-term benefits to farmers from conserving soil natural capital are small, whereas the potentially large long-term benefits have been difficult to quantify.

While many areas in soil science focus on end-of-pipe solutions and valuation of damages caused by destructive processes such as erosion, sealing and desertification, our study shows that insidious degradation of soil biodiversity and loss of supporting ecosystem services has consequences for agricultural productivity and resource use efficiency in the future. Therefore great care should even be taken to avoid losses of supporting ecosystem services on currently productive soils, and not just highly degraded soils, because the marginal user cost of degrading supporting ecosystem services will also be high. Economic efficiency therefore demands that soil natural capital be optimized on a field-by-field basis, which requires a valuation model that considers marginal changes in soil capital and is practical. We hope the approach presented here is a step in the right direction.

Online Supplemental Material

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The online Supplemental Material contains details of the model selection procedure, additional graphical analysis of the estimated production functions and validation of the modelled yields.

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Fig. 1. Wheat yield as affected by soil organic carbon concentration and fertilizer N input. Wheat production functions are based on data from long-term field experiments: (a) Scania, Sweden, (b) Bad Lauchstädt, Germany, (c) Askov, Denmark, and (d) Pendleton, Oregon, USA. Yield response (85% dry matter) is shown for increasing levels of mineral fertilizer input (x-axis) and soil organic carbon concentration (g C kg^{-1}), (higher curves). The shaded areas represent a continuum of curves for different SOC concentrations, within the range of SOC recorded at each site (Table 1).

Fig. 2. Same-yield contour lines associated with the production functions (kg ha^{-1}). These correspond to the isoclines of the production surface for each site shown in Supplemental Fig. S2.

Fig. 3. Future impacts of a one-off change in soil organic carbon concentration. (a) Absolute change in SOC concentration, and resultant change in: (b) optimal wheat yield, (c) fertilizer use efficiency, and (d) maximum profit every year in the future depending on the assumed current SOC concentration (i.e., **LOW**, **TODAY** or **HIGH**).

Fig. 4. The economic value of a marginal change in soil natural capital at each site as affected by the discount rate. The changes in annual profit underlying the present value calculations are: Scania 5.79 € ha^{-1}, Bad Lauchstädt 5.92 € ha^{-1}, Askov 2.36 € ha^{-1}, and Pendleton 0.47 € ha^{-1} (Fig. 3d, **TODAY** column).

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TABLES

Table 1. Overview of the four long-term data sets

		Units	Scania	Bad Lauchstädt	Askov	Pendleton
Observations		*No.*	485	84	144	558
Locations		*No.*	5	1	1	1
Time series	*start*	*Year*	1959	1957	2000	1931
	end	*Year*	2007	2009	2002	1992
Soil carbon†	*min*	*g kg^{-1}*	7.9	15.1	11.0	9.9
	max	*g kg^{-1}*	31.0	26.1	17.1	14.2
Fertilizer N	*min*	*kg ha^{-1}*	0	0	0	0
	max	*kg ha^{-1}*	150	100	180	90
Yield‡	*min*	*kg ha^{-1}*	710	2,320	1,572	1,210
	max	*kg ha^{-1}*	9,041	10,615	9,417	7,290

† The minimum and maximum concentrations found in the measured data excluding outliers.

‡ Yield is grain harvest weight at 85 to 86% dry matter.

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Table 2. Summary of experimental treatments at each site and the estimated annual rate of change in soil organic carbon content (*r*) brought about by each treatment. (Only summary statistics are presented for Scania due to the large number of functions for this site)

Site *(treatment ID)*	**Inorg Fert** *(kg N ha^{-1} yr^{-1})*	**FYM†** *(ton ha^{-1} yr^{-1})*	**Annual Change SOC‡** *(r×100) % Mean (SD)*	**Curve fit** *(Stat. Sign.)*	**SOC *Start*** *(g kg^{-1})*	**SOC *End*** *(g kg^{-1})*
A) Scania						
IIB0	0	0	-0.66 (0.19)	(4/5)§	10.8–30.9¶	9.3–22.8
IIB1	50	0	-0.46 (0.20)	(1/5)	10.9–32.9	9.9–22.4
IIB2	100	0	-0.36 (0.10)	(4/5)	11.0–33.9	10.5–25.2
IIB3	150	0	-0.29 (0.20)	(1/5)	11.1–32.9	11.0–26.4
IB0	0	5	-0.46 (0.16)	(5/5)	11.4–35.5	10.4–29.5
IB1	50	5	-0.19 (0.13)	(4/5)	11.2–33.7	11.3–27.6
IB2	100	5	-0.31 (0.14)	(4/5)	11.7–35.0	11.7–29.6
IB3	150	5	-0.23 (0.14)	(3/5)	11.5–32.8	11.6–26.8
B) Bad Lauchstädt						
18	0	0	-0.15	ns#	15.1	15.3
13	40–100	0	-0.03	ns	16.1	18.1
1	30–80	30	0.35	**	20.4	24.9
7	30–80	20	0.23	**	18.2	22.3
6	0	30	0.33	**	18.6	22.8
12	0	20	0.11	ns	17.8	20.0
C) Askov						
1a	0–180	0	0.84	na††	11.7	12.0
1b	0–180	0	-1.2	na	13.3	12.8
1c	0–180	0	-1.80	na	14.7	13.9
1d	0–180	0	-3.59	na	16.0	14.3
D) Pendleton						
2	0,45	0	-0.42	**	13.1	10.3
3	0,90	0	-0.37	**	13.2	10.7
4	34,45	0	-0.31	**	13.3	11.0
5	34,90	0	-0.29	**	13.0	11.2
6	0	0	-0.46	**	13.0	9.9
7	0	0	-0.34	**	12.8	10.4
8	0	22.4	0.02	ns	13.0	13.4
9	0	2.24	-0.24	**	13.3	11.9
0	0	0	-0.42	**	13.4	10.6

Notes: Statistical significance of parameter for annual percentage change in SOC concentration: ** = $P<0.05$ (the highest achievable with the non-linear estimation technique used), ns = not significant.

† The plant-available N from farm yard manure (FYM) has been taken into account in the determination of N input by assuming that 20% of N in FYM is available for crop growth in

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the year of application, which is subsequently included in the estimation of the production functions, i.e., N_input (variable *N*) = mineral N + 20% of N in FYM.

‡ Rate of change per unit time, *r*, according to Eq. (12).

§ Proportion of curve fits across all five sites with significant ($P<0.05$) change in SOC parameter.

¶ Range of minimum to maximum SOC concentrations across all five sites. Minimum concentrations correspond to the Örja site and maximum to the Ekebo site; a ranking which is maintained across all treatments and sub-sites.

Since SOC measurements were available for all years with wheat for Bad Lauchstädt (except one) it was not necessary to fit a curve to estimate missing SOC values, but are presented here as complementary information only.

†† Since the curve fits are based on only two years of SOC data, the start and end years, there is insufficient data to evaluate the curve fits statistically.

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Table 3. Best model selected from the suite of models fitted to the long-term data for each site and functional form; Quadratic (QUAD), Quadratic-Plus-Plateau (PLAT) and the Mitscherlich-Baule (M-B) functions.

	Model ID		Parameter‡ *i* 1	2	3	4	5	6	*k*¶	AIC#	AIC Wgt††
a) Scania											
QUAD	(1)	a_i	-5824.4***	40.42***	-0.118***	6077.9***	-951.3***	-4.17***	22	7787.2	**0.75**
PLAT	(1)	a_i	-7966.4*	40.32*	-0.109*	6082.7*	-923*	-4.72*	22	7789.4	0.25
M-B	(1)	b_i	4417.8*	0.016*	25.33*	1.54	10.44	na§	22	7867.8	0
b) Bad Lauchstädt											
QUAD	(8)	a_i	na†	50.34***	-0.37***	2180.7***	na	na	16	1425.2	**0.91**
PLAT	(8)	a_i	na	84.96*	-1.179*	2104.5*	na	na	16	1429.9	0.09
M-B	(1)	b_i	5421.0*	0.0279	3.479	3.392	3.479	na	18	1515.5	0
c) Askov											
QUAD	(7)	a_i	na	49.49***	-0.13***	3911.6***	-1018.2***	na	6	2191.3	**0.47**
PLAT	(7)	a_i	na	46.65*	-0.13*	5774.9	-1789.3	na	4	2521.9	0
M-B	(1)	b_i	9295.8*	0.010*	46.66*	12.06*	-0.93 *	na	6	2191.0	**0.53**
d) Pendleton											
QUAD	(3)	a_i	-6489.5***	105.04***	-0.077***	186.2***	na	-1.98***	66	8100.3	**0.99**
PLAT	(3)	a_i	-6324.6*	80.74*	-0.0166	182.6*	na	-1.51*	66	8109.1	0.01
M-B	(1)	b_i	11669.5*	0.015*	100*	0.043*	-18.242	na	66	8262.5	0

***, ** or * indicates the parameter is significant at the 0.001, 0.01 or 0.05 level respectively. NB: The parameters of the M-B model could only be evaluated at the 0.05 level due to the non-linear estimation technique.

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† na indicates the parameter was not included in the estimation for this model according to the model selection procedure (Supplemental Table S1).

‡ The parameters of each model are referenced according to their index $i = (1,6)$.

§ The M-B model does not have a parameter for $i = 6$ hence it is marked na.

¶ The number of parameters estimated in the model is k.

AIC is Akaike's Information Criterion.

†† The model with the highest AIC weight is the best choice according to this criterion (shown in bold).

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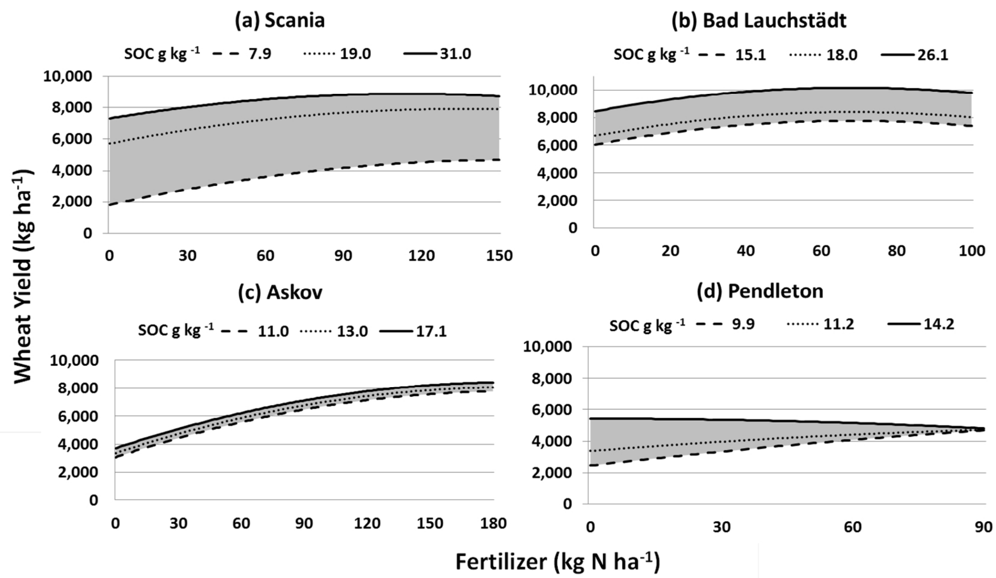

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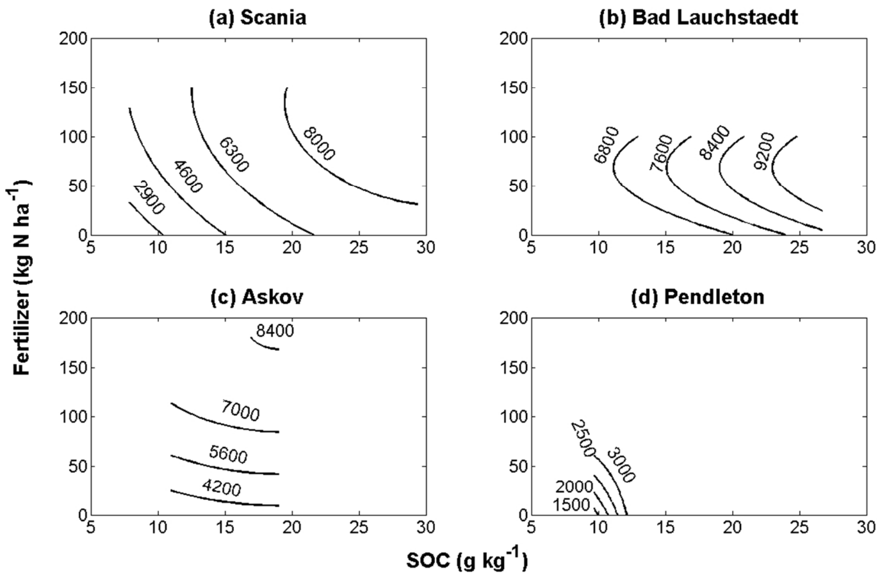

Fig. 2. Same-yield contour lines associated with the production functions (kg ha^{-1}). These correspond to the isoclines of the production surface for each site shown in Supplemental Fig. S2.
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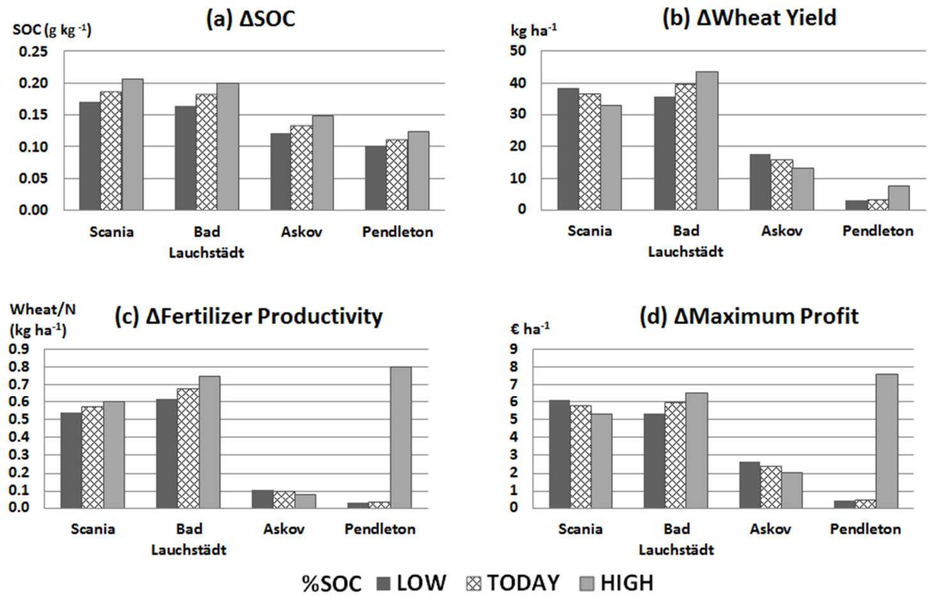

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339x206mm (72 x 72 DPI)

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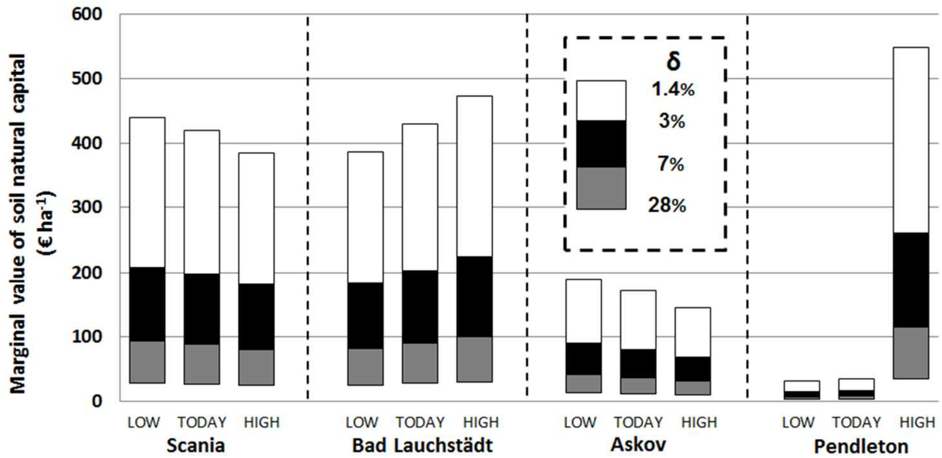

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329x153mm (72 x 72 DPI)

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SUPPLEMENTAL MATERIAL

Valuing Supporting Soil Ecosystem Services in Agriculture: a Natural Capital Approach

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This material comprises 12 pages, four tables and two figures.

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MODEL SELECTION CRITERIA AND EVALUATION

In this section we present the models selected for estimation, the AIC values (Akaike, 1978) for the estimated models and extended graphical analysis for the models identified in Table 3 based on the quadratic function (the most successful form).

Models selected for estimation

The models selected for estimation based on the theoretical quadratic, quadratic-plus-plateau functions, and M-B function are specified in Table S1.

Table S1. Models selected for estimation based on the Quadratic (including the Quadratic-Plus-Plateau) and Mitscherlich-Baule funtional forms. A 1 means the parameter was included in the estimation and 0 that it was excluded.

Model	*Quadratic functions (Eqs.1 to 3)*						*M-B function (Eq.2)*				
ID	a_1	a_2	a_3	a_4	a_5	a_6	b_1	b_2	b_3	b_4	b_5
(1)	1	1	1	1	1	1	1	1	1	1	1
(2)	0	1	1	1	1	1	1	1	1	1	0
(3)	1	1	1	1	0	1	1	1	0	1	1
(4)	0	1	1	1	0	1	1	1	0	1	0
(5)	1	1	0	1	0	1	1	1	1	0	0
(6)	0	1	0	1	0	1	1	1	0	0	0
(7)	0	1	1	1	1	0	1	0	0	1	1
(8)	0	1	1	1	0	0	1	0	0	1	0
(9)†	na	na	na	na	na	na	1	0	0	0	0

† na: not applicable

AIC Values and significance of parameters

The AIC values for the 8 different quadratic models (the most successful functional form) are shown in Table S2. The quadratic and quadratic-plus-plateau provide fairly similar fits to the data sets for all sites. Compared to the quadratic, the quadratic-plus-plateau model adds a

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restriction; it is based on the premise that yield will not decline as a consequence of excessive nutrient inputs. The data for Scania and Bad Lauchstädt show a decreasing trend for yield when N input reaches a critical level; which explains why the plateau model was not suitable for these sites. The advantage of the M-B function is that it allows for nutrient saturation and asymptotic maximum yield (it isn't forced to bend down), which has intuitive appeal. But it has disadvantages (Frank et al., 1990): it doesn't allow for possible yield depression for extreme nutrient levels, nor does it allow for an initial stage of increasing returns or a final stage of decreasing returns for an added input; and—crucially for this research—it only allows for limited substitution between inputs, which could be expected when modeling the effects of different nutrients, e.g., fertilizer N and P on yield, but not necessarily for fertilizer and SOC.

The function having the minimum AIC that was at least 2 units lower than the other candidates (Table S2) was chosen directly as the best fitting model for this functional form and transferred to Table 3 in the main text. This was so for Scania; the full quadratic model was the best choice and all parameters are significant at the highest level. For the other sites, no single model satisfied the minimum AIC criterion. Therefore the parameters of the models with equivalently low AIC values were transferred to Table S3; for Bad Lauchstädt models (4), (7) and (8); Askov (2), (5) and (7); and Pendleton (1) and (3), and the best model for each site was selected based on the highest AIC weight. In this way the best model was selected from the suite of models based on each of the quadratic, quadratic-plus-plateau, and Mitscherlich-Baule (M-B) models and transferred to Table 3.

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Table S2. AIC values for the suite of models based on the quadratic function.

Equivalently best model(s) based on the minimum AIC values are marked in bold and transferred to Table S3.

Function	Scania	Bad Lauchstädt	Askov	Pendleton
Obs.	*485*	*84*	*144*	*558*
(1)	**7787.22**	1429.74	2194.46	**8101.32**
(2)	7955.91	1428.56	**2193.14**	8113.30
(3)	7820.84	1429.06	2194.50	**8100.31**
(4)	7955.64	**1427.15**	2201.40	8417.39
(5)	7899.22	1429.45	**2291.31**	8112.30
(6)	8029.53	1430.59	2296.28	8427.35
(7)	7810.42	**1427.21**	**2191.26**	8185.44
(8)	7853.25	**1425.21**	2210.60	8416.50

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Table S3. Models with equivalently low AIC values for the suite of quadratic functions estimated for each site. The best model was selected on the basis of the highest AIC weight (which is marked in bold and transferred to Table 3).

	Parameter, a_i =								AIC
Model ID	*1*	*2*	*3*	*4*	*5*	*6*	*k*	**AIC**	**wgt**
Bad Lauchstädt									
(4)	na†	52.66**	-0.34**	2207.8**	na	-2.43	17	1427.15	0.22
(7)	na	50.27***	-0.37**	2196.9**	-8.48	na	17	1427.21	0.21
(8)	na	50.34***	-0.37***	2180.7***	na	na	16	1425.21	**0.57**
Askov									
(2)	na	47.65***	-0.13***	4032.2***	-1106.7**	1.36	7	2193.14	0.17
(5)	2400**	25.04**	na	1083.0	na	0.85	6	2191.31	0.41
(7)	na	49.49***	-0.13***	3911.6***	-1018.2***	na	6	2191.26	**0.42**
Pendleton									
(1)	-8781***	104.56***	-0.08***	288.4**	-1.13	-1.97***	67	8101.32	0.38
(3)	-6489***	105.04***	-0.08***	186.2***	na	-1.98***	66	8100.31	**0.62**

***, ** or * indicates the parameter is significant at the 0.001, 0.01 or 0.05 level respectively.

† na indicates the parameter was not included in the estimation for this model according to the model selection procedure in Table S1.

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EXTENDED GRAPHICAL ANALYSIS AND VALIDATION OF MODELLED YIELD

In Fig. S1 we graph for each site the best model for each functional form reported in Table 3 for a visual comparison. All curves are plotted over the range of nitrogen applied at each particular site and according to SOC concentrations in Table S1 column "SOC End": Scania 19.0 g C kg^{-1} (average of Treatment IIB3); Bad Lauchstädt 1 8.0 g C kg^{-1} (Treatment 13); Askov 13.0 g C kg^{-1} (average of Treatments 1b and 1c); and Pendleton 11.2 g C kg^{-1} (as measured for Treatment 5 in 1986). The year effect is included for the benchmark year according to Table S4. As can be seen all models predict similar maximum yield and similar minimum fertilizer input to achieve this yield. The slope of the M-B curve is however somewhat different than those for the quadratic functions for Bad Lauchstädt, implying that the economic optimal N input could be affected by the choice of function (which would be an important consideration when giving advice to individual farmers). Naturally the slopes of the quadratic and quadratic-plus-plateau curves are similar among all sites. Recall though that the M-B function proved to be the least plausible for both Bad Lauchstädt and Scania, and according to the AIC weight the quadratic function is the best overall choice.

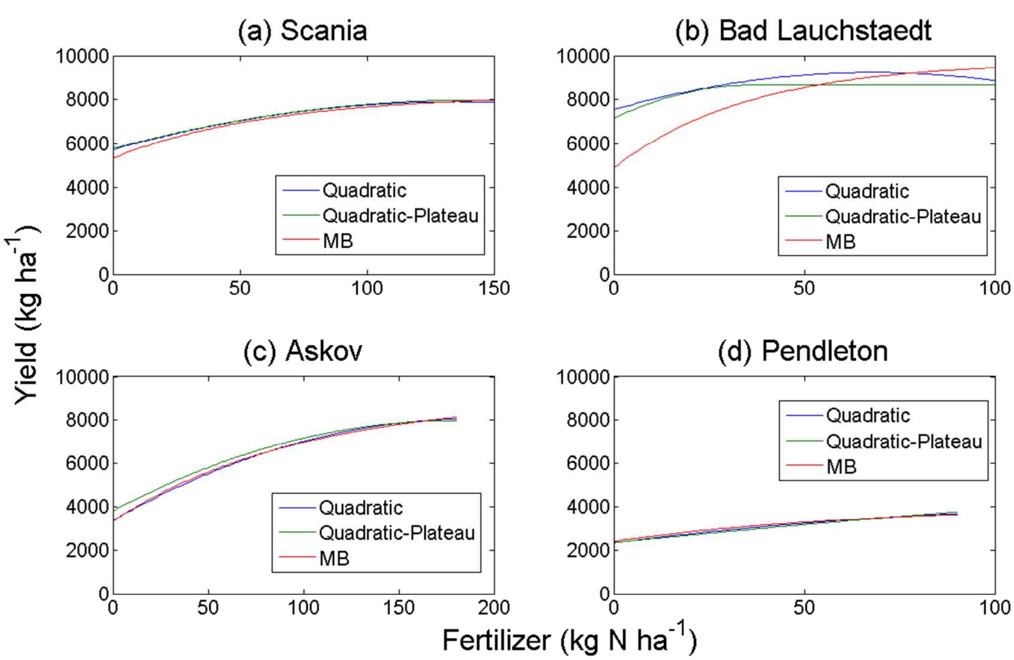

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Fig. S1. Comparison of the best-fit Quadratic, Mitscherlich-Baule and Quadratic-Plus-Plateau models for each site specified in Table 3 of main article.

In Fig. S2 we plot the entire production surface for the best-fit quadratic function for each site. Wheat yield is shown for all combinations of nitrogen fertilizer and SOC present in the underlying data (with the year effect according to the benchmark year specified in the note to Table S4). The production surfaces show similar general patterns among the sites but maximum yield and response to carbon differ, which is attributable to site specific characteristics. Thus changes in SOC indicate a relative change in the stock of natural capital at a particular site. It is this surface that makes it possible to estimate the effects of changing SOC on yield and fertilizer use efficiency. The production functions shown in Fig. 1 of the main text are simply cross-sections of the surface taken at different levels of SOC, with the outer curves in Fig. 2 being those for the minimum and maximum levels of SOC measured over the course of each experiment.

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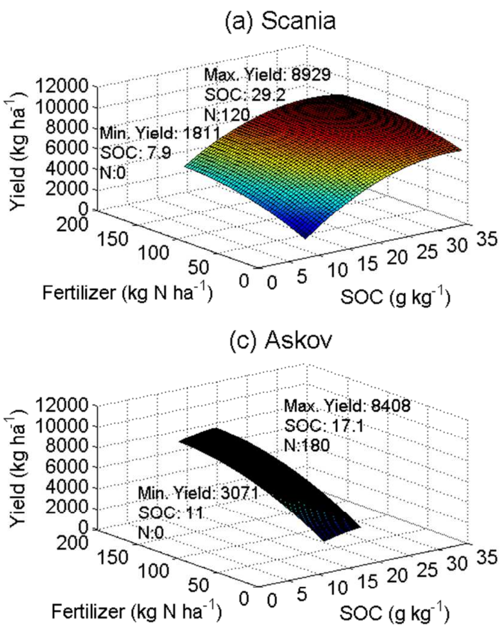

Fig. S2. Plots of the production surface for the quadratic model for each site.

Validation of modeled yields

The production functions have been modeled using time series data, which necessitates the consideration of potential year effects (see **Estimation Procedures** in main text). To compare the similarity of the maximum yield predicted by the estimated production functions (Figs. 1 and S.2) with observed yields we needed therefore to select a reference or benchmark year and include the year effect for that particular year in the model (which affects the height or intercept of the production function). Due to the limited range of years present in the Askov data we selected the year 2000 (or closest year to it for which we have data) for benchmarking the production functions.

In Table S4 we compare the maximum and minimum observed yields at each site—for both the entire dataset (*All years*) and for the benchmark year (*Benchmark*)—to the modeled maximum and minimum yield for each site. The differences between the observed and

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modeled yields are a result of the linear regression procedures, with the modeled yields lying between the extremes of the observed yields. This is consistent with the modeled yields reflecting normal or average yields. For all sites the modeled maximum yield is lower than the observed maximum yield across all years, and the modeled minimum yield is higher than the observed minimum yield across all years. Therefore we can conclude that the modeled yields are reasonable in comparison to the observed ranges of yields.

Table S4. Comparison of maximum and minimum observed yields to modeled yields

		Observed yield		**Modelled**
Site		*All years*	*Benchmark†*	**Yield**
Scania	Max	9041	8908	8929
	Min	710	1831	1811
Bad Lauchstädt	Max	10615	9303	10370
	Min	2320	6865	5954
Askov	Max	9417	9417	8408
	Min	1572	2641	3071
Pendleton	Max	7290	4620	4426
	Min	1210	2480	1284

† Year of benchmarking for Scania is 1999, Askov 2000, Bad Lauchstädt 2001 and Pendleton 1992.

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DERIVATION OF YIELD MAXIMIZING FERTILIZER INPUT AND SOC

The full quadratic function in two variables where N (kg ha^{-1}) is input of plant available nitrogen and C is percent SOC content according to Eq. (1) is

$$Y(C,N) = a_1 + a_2N - a_3N^2 + a_4C - a_5C^2 - a_6NC. \tag{S.1}$$

In this equation only a_1 and a_6 can take on any sign, all other parameters $a_2,...,a_5$ should agree with the shown signs to comply with regularity conditions for a crop production function. Since the yield function Eq. (S.1) is concave the optimality conditions for maximum yield are:

$$\frac{\partial Y(C,N)}{\partial N} = a_2 - 2a_3N + a_6C \tag{S.2}$$

$$\frac{\partial Y(C,N)}{\partial C} = a_4 - 2a_5C + a_6N. \tag{S.3}$$

For a maximum both equations need to be zero and the determinant of the Hessian $Y_{NN}Y_{CC} - Y_{CN}{}^2 > 0$ and $Y_{NN} < 0$ (where the subscript N means differentiation with respect to N and C means differentiation with respect to C).

These equations give two different solutions since a_5 is zero if no quadratic term for C is considered. We have to solve the system

$$\left.\begin{aligned} 2a_5C - a_6N &= a_4 \\ -a_6C + 2a_3N &= a_2 \end{aligned}\right\}. \tag{S.4}$$

Multiplying the top equation by a_6 and the bottom equation by $2a_5$ we can sum the equations and solve for N: we get $\bar{N} = (2a_2a_5 + a_4a_6)/(4a_3a_5 - a_6^2)$. Performing a similar trick, namely multiplying the top equation by $2a_3$ and the bottom equation by a_6 we can sum the equations and solve for C: we obtain $\bar{C} = (2a_3a_4 + a_2a_6)/(4a_3a_5 - a_6^2)$. Given this, maximum possible

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yield is calculated by substituting $\bar{N}$ and $\bar{C}$ into the yield function we find

$Y_{\max} = a_1 + (a_2^2 a_5 + a_2 a_4 a_6 + a_3 a_4^2)/(4a_3 a_5 - a_6^2)$ which is a maximum if $4a_3 a_5 \geq a_6^2$.

This last condition stems from the condition that for a maximum the determinant of the Hessian should be greater than 0, while the second derivative with respect to *C* (or *N*) should be negative.

Maximum Yield for Bad Lauchstädt

For Bad Lauchstädt the marginal physical productivity of C is positive over the entire range of observed values for *C* and *N* (becoming zero when $N = -a_4/a_6$) hence the solution will be on the border of the relevant space. There are two candidates for a maximum: the border solutions where $\bar{C} = 0$ or $\bar{C} = C_{\max}$. It is obvious that $\bar{C} = C_{\max}$ must maximize yield, therefore

$$N^* = \frac{a_2 + a_6 C_{\max}}{2a_3}. \tag{S.5}$$

Maximum yield is calculated by substituting N^* and $C_{\max}$ into the yield function.

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Supplemental References

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