Managing soil natural capital: An effective strategy for mitigating future agricultural risks

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Managing soil capital: an effective strategy for mitigating future agricultural risks?

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Abstract

Uncontrollable events such as adverse weather and volatile prices present considerable risks for arable farmers. Soil capital, which views the soil as a component of farm capital, could be important for the stability and resilience of arable production systems. We investigate therefore whether managing soil capital could be an effective strategy for mitigating future agricultural risks. We do this by constructing a dynamic stochastic portfolio model to optimize the stock of soil organic carbon (SOC)—our indicator of soil capital—when considering both the risk and return from farming. SOC is controlled via the spatial and temporal allocation of cash crops and an illustrative rejuvenating land use (grass fallow). We find that higher soil capital buffers yield variance against adverse weather and reduces reliance on external inputs. Managing soil capital has therefore the potential to mitigate two serious agricultural risks: price shocks and negative weather events, both of which are likely to be exacerbated in the future through, e.g., globalization and climate change.

Keywords: *soil capital*Copula model; dynamic portfolio theory; soil conservation; soil organic carbon; sustainable agriculture; yield response function

1. Introduction

Consideration of risk is pivotal for farmers when making agricultural management decisions (Chavas and Holt, 1990; Leathers and Quiggin, 1991). The major risks confronted are production risk due to uncontrollable events such as adverse weather or attacks by pests and pathogens, and market risk due to uncertainty about future input and output prices (Pannell *et al.*, 2000; Moschini and Hennessy, 2001). Adverse weather such as drought, excessive moisture, hail, frost and flooding accounts for a high proportion of yield losses (Vergara *et al.*, 2008). Arguably the capacity to adapt to weather variation will be increasingly important for farmers in the face of climate change (Wall and Smit, 2005). Further, farmers all over the world are becoming increasingly exposed to volatile global markets. Seasonal variation in input and output prices can be predicTable but much price variation is dependent on unforeseeable shocks to both supply and demand (de Janvry and Sadoulet, 2010; Derek, 2011) or on variation in the quality of products (Hueth and Ligon, 1999; Larsen and Asche, 2011).

The most common methods used by farmers to mitigate risk are crop diversification (e.g., cultivate more than one crop at the same time) and risk sharing through the purchase of financial instruments (Jain and Parshad, 2006). Crop diversification requires low correlation between crop prices or yield responses to weather events and has in this sense similarities to choosing a portfolio of securities (Markowitz, 1959; Di Falco and Perrings, 2005). Farmers can also share risks with others by purchasing financial instruments, e.g., the Federal Crop Insurance Program in the USA (Goodwin *et al.*, 2004; Vedenov and Barnett, 2004). Forward and future contracts can be used to fix the selling price at a specified date, whereas an option gives the farmers the right, but not the obligation, to sell their output at a reference price and date (Tomek and Peterson, 2001).

A less understood option is the role *soil capital* and associated ecosystem services play in the control of agricultural risks. In natural ecosystems the soil functions as a dynamic regulator whereby species-rich organism communities (or soil biodiversity) influence the magnitude and temporal distribution of carbon and nutrients, particularly nitrogen and phosphorous, and hence the prospects for plant growth under different weather conditions.

In contrast, in intensive-farming systems biological regulation is largely replaced by mechanical soil management (e.g. the no-tillage management is mainly used for the control of diseases) (Llewellyn *et al.*, 2012), mineral fertilizers (e.g. to replace nutrients removed through harvested products) and chemical pesticides. In these systems the soils' capacity for self-regulation is therefore reduced and greater dependence is placed on purchased inputs (Swift *et al.*, 2004). Despite this simplification, even the most intensively farmed agricultural soils still house complex biological communities that generate a wide range of supporting *ecosystem services* that underpin agricultural productivity, particularly nutrient cycling, nitrogen fixation, phosphorus acquisition, decomposition of organic materials/mineralization of carbon, soil structure modification, moisture regulation, and pest and disease control (Altieri, 1999; Barrios, 2007). These ecosystem services tend to be degraded over time through intensive production (Bommarco *et al.*, 2013).

Recently, n*atural capital* has emerged as a framework for internalizing the value of ecosystem services in decision-making (Sukhdev *et al.*, 2010; Kareiva *et al.*, 2011). Because ecosystems can generate a flow of beneficial services over time they are, from an agricultural production perspective, no different from other assets, and should therefore be managed in a similar manner (Barbier, 2007; Turner and Daily, 2008). Managing soil capital might therefore be an additional method to mitigate production risk as higher abundances and diversity of soil organisms increases both the generation and reliability of soil ecosystem services (Koellner and Schmitz, 2006). Soil capital may also reduce market risk because ecosystem services can substitute for costly inputs such as mineral fertilizers, pesticides and energy (Thrupp, 2000; Weitzman, 2000; Figge, 2004).

Knowledge is however lacking about the potential of soil capital to reduce agricultural risks (Brussaard *et al.*, 2007), rather the focus of research has been on top-soil conservation and its expected economic benefits (Burt, 1981; Goetz, 1997; Pretty *et al.*, 2011; Bommarco *et al.*, 2013; Paul *et al.*, 2013). Here we investigate whether managing soil capital, as represented by the stock of soil organic carbon (SOC), can mitigate agricultural risks.

Although we recognize the complexity of the relations between soil organisms and soil ecosystem services (ES), knowledge of the direct links between them is sparse (Bardgett *et al.*, 2005; de Vries *et al.*, 2013). For this reason, an approximation is necessary for informing management decisions. It is widely accepted that SOC is a major factor in a soils overall health and agricultural productivity (Johnston *et al.*, 2009; Lal, 2010). This is because the utilization of soil organic matter as a substrate of energy by soil organisms underpins the generation of soil ecosystem services (Bauer and Black, 1994) and, consequently, loss of organic carbon will diminish a soil's capacity to generate services. The carbon content of a soil is also related to the size, complexity and functioning of soil food webs (de Ruiter *et al.*, 2005). Therefore a change in SOC content can be used as a proxy for changing stocks of soil capital.

We assume a uniform soil type (i.e., clay soil) to avoid confounding the results. It is straightforward to extend the model to multiple soil types (i.e., varying clay/sand content) and hence derive optimal SOC for each type. Thus this is a modeling assumption to avoid unnecessary complexity.

Although soil capital has the potential to reduce agricultural risks, there are few studies that actually evaluate it (Schläpfer *et al.*, 2002; Koellner and Schmitz, 2006), and none in respect of arable farming. Di Falco and Perrings (2005) and Di Falco and Chavas (2008;

2012) studied how spatial crop diversity could be used to mitigate agricultural risk. Our article goes beyond spatial diversification (and crop rotations generally) by incorporating the role of soil capital in reducing agricultural risk exposure, which is affected by farming choices over time. Therefore, while a static approach is sufficient for analyzing the crop diversification problem our analysis requires a dynamic model to link past cropping decisions to the current stock of SOC.

On the other hand, there is an extensive literature that applies modern portfolio theory to the crop diversification problem (Moschini and Hennessy, 2001; Nalley and Barkley, 2010; Rădulescu *et al.*, 2011). The first application goes back to Freund (1956) who measured the risk of an agricultural enterprise as the variance of its returns, hence showing quadratic programming could be used for determining optimal crop allocations incorporating risk. Hazell (1971) changed the risk measure of farm returns to the mean absolute deviation. As a result the crop diversification problem could be formulated as a linear programming problem (Brink and McCarl, 1978). However, in practice the covariance matrix is infeasible to estimate or unknown due to paucity of data, and it can only capture linear relationships (Pafka and Kondor, 2003; MacLean *et al.*, 2007). In our study it is crucial to capture potentially correlated weather and market risks.

Consequently to model the potential for soil capital—a stock variable (i.e., SOC here)—to control risks a number of innovations were required. First, a copula function is introduced to model the dependence structures of stochastic weather variables relevant to crop yields (Woodard *et al.*, 2011) and stochastic input and output prices (Serinaldi, 2009; AghaKouchak *et al.*, 2010) which makes it possible to calculate both the expected profit and concomitant risk generated by a particular crop portfolio (via the variance of expected profits).

Second, we estimate crop production functions (e.g., Frank *et al.*, 1990) that predict crop yields based on fertilizer input, the state of SOC and weather outcomes. Many articles focus on the relationship between yields and nutrient inputs (primarily N, P, and K), and moisture and temperature (Ackello-Ogutu *et al.*, 1985; Malik and Sharma, 1990; Muchow *et al.*, 1990; Halvorson and Reule, 1994), but few address the relationship between yield, SOC and the weather based on yield functions (Lal, 2006; Benbi and Chand, 2007). To predict the effects of changes in soil capital and associated ecosystem services on crop yield, we link crop yield to fertilizer input and the stock of SOC by estimating production functions with data from long-term agricultural field experiments (see supplemental online material A). We extend this approach to include even weather variables, thus making it possible to examine changes in expected yield and its variance given simulated price and weather in the future. Finally, we extended the traditional static portfolio model to a dynamic setting to analyze the effects of managing (i.e., conserving or depleting) SOC on expected farm profits and risk.

The logical relationships among models and data flows are shown in Fig. 1. In the next section we specify the dynamic portfolio model. A numerical case is then analyzed based on data from a typical arable cropping region in northern Europe.

[Insert Fig. 1 here]

2. The portfolio model

We begin by developing the static portfolio model as a benchmark, after which we extend it to a dynamic setting, with both considering weather and market risks. Consider a farm comprising a set of arable fields $j \in \{1, 2, ..., m\}$ that are located within the same climate zone such that all fields are subjected to identical stochastic weather events. The area of field *j* is S_j (ha). The stock of SOC associated with field *j* is C_j (% SOC) which is included in the model as a state variable. SOC content is assumed to be homogeneous within each field but can vary among fields. The other variables of the model are:

F_i - fertilizer input for crop *i* (kg ha^{-1})

E_i - energy input for crop *i* (liter ha^{-1}).

P_F - the stochastic price of fertilizer (€ kg^{-1})

P_E - the stochastic price of energy (€ unit^{-1})

x_{ij} - the decision variable representing the proportion of land used for crop *i* on field *j* such that $\sum_{i=1}^{n} x_{ij} \leq 1$

W - the stochastic weather variables (e.g. rainfall and temperature)

b_i - the stochastic price of crop *i* (€ kg^{-1})

a_i - other constant unit production costs for crop *i* (€ kg^{-1}) including costs of fertilizer, energy, labor, etc.

The yield response of crop *i*, Y_{ij}, to fertilizer N input on field *j* depends on the weather, W, and the state of SOC, C_j, such that $y_{ij} = Y_{ij}(W, C_j)$ which is specified below in Section "Yield response".

2.1 Static portfolio model

The farmer's objective is to choose a production plan for each field from the set of possible crops $i \in \{1, 2, ..., n\}$. The gross margin (π) obtained by the farmer is:

$$\pi(x, y) = \sum_{i=1}^{n}\sum_{j=1}^{m} b_i y_{ij} x_{ij} S_j - \sum_{i=1}^{n}\sum_{j=1}^{m} (a_i + P_F F_i + P_E E_i) S_j x_{ij} \qquad (1)$$

where the first expression is total revenue and the second total cost.

The static portfolio model is consequently:

$$\text{Max } Ex\ (\pi(x, y)) \tag{2}$$

s.t.

$$\begin{aligned}
&Var(\pi(x, y)) \leq \phi\, Var_{\max}(\pi(x, y)) && -\ \text{Risk constraint} \\
&\sum_{i=1}^{n} x_{i,j} \leq 1 && -\ \text{Land constraint} \\
&\sum_{j}^{m} x_{i,j} S_j \leq \sum_{j=1}^{m} S_j rot_i && -\ \text{Rotation constraint}
\end{aligned} \tag{3}$$

where $Ex(\pi)$ refers to the expected profit and *Var(π)* is the variance of profit. The risk constraint implies that the maximum acceptable variance is $\phi Var_{\max}(\pi)$, where ϕ is a parameter that can be controlled to represent different levels of risk tolerance. The land constraint ensures that the area used for growing crops does not exceed the availability of land. Land that is not used for growing a marketable crop, i.e. the land constraint is slack, is assumed to be planted with a grass fallow with zero mean profit and variance. Its opportunity cost is the loss in agricultural profit from fallowing the land. Finally, the rotation constraint ensures that the area sown to a particular crop does not exceed the maximum percentage of total area (rot_i) that can be used for crop *i* in the region (e.g., to avoid diseases or comply with production quotas).

The principle of the portfolio model is to show the tradeoff between risk and profit (Rădulescu *et al.*, 2011). For each ϕ there is a maximum expected profit and corresponding efficient crop-portfolio that satisfies the risk constraint (i.e., maximum tolerable variance). For the efficient portfolio it doesn't matter whether the goal is to maximize profit under a risk constraint or to minimize risk under a profit constraint; the problems are equivalent (Haugen and Haugen, 2001). Furthermore, we only consider the second derivative of profits as a measure of risk (i.e., the variance), thus ignoring higher moments of the distribution (e.g., skewness). Therefore, the classic portfolio model (i.e. (2) and (3)) serves the purposes for our research.

2.2 Dynamic portfolio model

The dynamic portfolio model is created by introducing the time variable *t*, and the state-transformation function for SOC as follows:

$$\text{Max Ex}\ (\sum_{t=1}^{5} \pi(x,y)(1-\delta)^{t}) \tag{4}$$

s.t.

$$\begin{aligned}
&Var(\sum_{t=1}^{5}(\pi(x,y)\times(1-\delta)^{t})) \le \phi\, Var_{\max}(\sum_{t=1}^{5}(\pi(x,y)\times(1-\delta)^{t})) && -\text{Risk constraint}\\
&\sum_{i=1}^{n} x_{i,j,t} \le 1 && -\text{Land constraint}\\
&\sum_{j}^{m} x_{i,j,t} S_j \le \sum_{j=1}^{m} S_j rot_i && -\text{Rotation constraint}\\
&C_{j,t} = C_{j,t-1} + (1-\sum_{i=1}^{n} x_{i,j,t-1})\gamma + \sum_{i=1}^{n} x_{i,j,t-1}\lambda_i && -\text{Soil capital state transformation}
\end{aligned} \tag{5}$$

where in equations (4) and (5): δ is the discount rate, γ the annual rate at which SOC regenerates when grass fallow is used and λ is the annual rate of SOC depletion associated with crop production. The values for γ and λ are set to 1% and -0.5% based on empirical experiences. Consequently, in the dynamic model, land planted to the regenerative land use is assumed to rejuvenate soil capital (i.e., a grass fallow). In practice, there exists a diversity of different practices or combinations of them that could be used to manage SOC including incorporation of stable manure or other organic amendments, cover crops and green manure or low tillage regimes (Paustian *et al.*, 2000; Dobermann and Cassman, 2002; Lal *et al.*, 2004). For clarity we focus only on a representative measure; grass fallow. The risk constraint in the dynamic model restricts the variance of the net present value of accumulated profits over five periods to a specified level. There are some reasons why we choose to optimize over only five periods: first the price and weather risks we model are based on historical data (about fifty years), so we can only forecast the risks in the near future; and second our principle aim is to establish whether SOC can be managed to control agricultural risks and how to go about evaluating its potential. In this sense, we need only simulate the general trends in the emerging distributions of farmers' profits given different management choices over time. Therefore the optimization across five periods is enough at this stage.

3. Data sources and sub-models

This section describes the sources of data and sub-models used to generate inputs for the portfolio models. First, the case-study region is introduced; second, the Copula method used to model potential dependencies in the weather and price time-series is described; third, the yield response functions are estimated based on the panel data; and finally, initial settings for the models are presented.

3.1 Case-study region

The case study region is the arable cropping region Scania in southern Sweden. It has a temperate European climate with rainfall and temperature being the most important weather factors affecting crop yields (Wilhelm and Wortmann, 2004; Lobell *et al.*, 2007). The soil is also highly fertile, which combined with the generally favorable climate for arable cropping, makes for an average wheat yield (under normal weather conditions) of almost 8 t ha^{-1} but yields can exceed 10 t ha^{-1}. The four main crops grown in Scania are winter wheat, spring barley, sugarbeet and winter rapeseed which together cover almost 70% of the arable land area (SCB, 2011). Lack of organic amendments, such as farmyard manure, break crops, green manure, etc., results in declining SOC content (Johnston *et al.*, 2009). The method to measure SOC can be found in Carlgren and Mattsson (2001). We use the data from five proximate sites (Ekebo, Fjärdingslöv, Orup, Södra Ugglarp and Örja) in Scania from 1957 to 2009. The total amount of samples is 1568. Each sample consists of 10 subsamples from each experimental square down to 20 cm. The top cm of soil is scraped away from each sample.

3.2 Modeling weather risk using the Copula method

The Copula model (Schölzel and Friederichs, 2008) is introduced to describe the joint probability distributions of monthly temperature and rainfall in Scania resulting from seasonal dependence between them (Shukla and Misra, 1977). For clarity, we introduce the copula process and results briefly, but full details can be found in Cong and Brady (2012). Let X and Y denote two continuous random variables representing temperature and rainfall, with distribution functions $F(x) = \Pr(X \le x)$ and $G(y) = \Pr(Y \le y)$. Following Sklar (1959), there is a unique function C (a Copula) such that:

$$\Pr(X \le x, Y \le y) = C(F(x), G(y)) \tag{6}$$

where $C(u,v) = \Pr(U \le u, V \le v)$ is the distribution of the pair $(U,V) = (F(X), G(Y))$. C characterizes the dependence between the pair (X,Y) (Joe, 1997; Nelsen, 1999). To choose C, five families of commonly used copulas are considered. Their parameter ranges are listed in Table 1; the first three are Archimedean and the last two meta-elliptical copulas (Fang *et al.*, 2002). The parameter θ governs dependence. After calculating the parameters of each copula, the family best representing the dependence is selected according to the Akaike (AIC) and Schwarz's Bayesian (BIC) Information Criteria (Patton, 2009).

[Insert Table 1 here]

To illustrate the model selection procedure we use the rainfall and temperature data obtained from the Swedish Meteorological and Hydrological Institute for April (Cong and Brady, 2012). Based on the inference for margins (IFM) technique (Joe and Xu, 1996), related evaluation indices are listed in Table 2. The log-likelihood for Student Copula (4.11) is the largest while the AIC and BIC for Student Copula are smallest, hence the Student Copula model is the best model according to these criteria, which is also supported by the residuals' scatter graph (Fig. 2).

[Insert Table 2 here]

[Insert Fig. 2 here]

3.3 Modeling price risk using the Copula method

A six-variable Copula model is constructed to simulate the dependencies among the different price series for the four cash crops, and fertilizer and energy inputs over the period 1966 to 2010 (SCB, 2012). The model evaluation indices are shown in Table 3. The log-likelihood of Student Copula is largest while the AIC and BIC for the Student Copula are smallest, which implies that the Student copula model is best.

[Insert Table 3 here]

3.4 Yield response

In southern Sweden arable crops are rain-fed, hence the availability of moisture and avoidance of water-logging during the growing season is critical for crop production

(Hammar, 1990). Total rainfall over the growing season for each crop is therefore used to model the yield response to rainfall. For spring sown crops only temperature over the growing season is important (i.e., as an indicator of warmth, sunlight, etc.). Autumn sown crops need to overwinter, particularly to survive freeze-thaw events; consequently temperatures over the entire production period are relevant for these crops.

The general crop yield response function is specified as:

$$\begin{aligned} Y(C,N,rain,temp) &= a_1 + a_2 N + a_3 N^2 + a_4 C + a_5 C^2 + a_6 NC \\ &+ a_7 rain + a_8 rain^2 + a_9 temp + a_{10} year \end{aligned} \tag{7}$$

The variables *N* and *C* denote nitrogen (kg/ha) and soil organic carbon (% SOC); *rain* and *temp* denote total precipitation (mm) and average temperature (degrees Celsius) over the critical months (Table 4); and *year* is the observation year. We also consider the potential substitution effect between SOC and nitrogen via the interaction term, NC . If the parameter of interaction term, a_6 , is negative, the substitution effect is proven, which means that depletion of SOC will need extra N input. Based on the historical data (See supplementary online material B) for Scania, panel data models with fixed effects (Baltagi, 2008) are employed to estimate the yield response function (7) for the four major crops (Table 5). In the yield response functions, we tried to analyze the interaction effects of temperature and rainfall (i.e. $rain \times temp$) and temperature and SOC (i.e. $C \times temp$). But they are not statistically significant. We believe that is because the temperature in Southern Sweden is moderate. However, it is interesting to test the possible interaction effects in other regions in the future studies.

[Insert Table 4 here]

[Insert Table 5 here]

3.5 Initial settings

Twenty fields of 1 ha each are initialized in the landscape which is sufficient to represent the variation in SOC across fields in this region. The simulation period for the dynamic model is set to five years. Based on carbon measurements from typical fields in Scania (Söderström, 2012), the mean ($mean_c$) and stand deviation (sd_c) of SOC are set to 1.78 (% SOC) and 0.54 respectively. The SOC samples are randomly generated as shown in Fig. 3.

[Insert Fig. 3 here]

Crop rotation constraints—by which we mean the permissible sequences of crops that can be grown on a particular field over time—are based on the normal practices for this region to control the spread of crop pests and diseases (Table 6). Here we use the maximum percentage of the total arable area that may be planted with a particular crop in any year, instead of the explicit rotation over time, in order to model the average effect of the rotation constraint.

[Insert Table 6 here]

4. Empirical results: optimal crop diversification and soil capital management under multiple risks

Initially results of the static model are reported to identify the pure portfolio effect of crop diversification. Subsequently, the dynamic model is presented to determine the combined effect of the crop portfolio and management of soil capital (i.e., SOC).

4.1 Static results

We analyze the portfolio effect and its operating mechanisms from two standpoints. First, the efficient frontier is analyzed to determine the relationships between profit and risk.

Second, cropping patterns and corresponding economic results are explored for different levels of risk.

4.1.1 Static efficient frontier

According to the static frontier the maximum mean profit is €11.9k and the associated risk, as measured by the variance of the profit is, €^{2} 12.5k. The simulated static efficient-frontier is plotted in Fig. 4 and divides the figure into the infeasible space and inefficient space. Data points on the efficient frontier are both feasible and efficient while points in the infeasible space could be preferable but it is not possible to achieve such high profits given the risk. Points in the inefficient space are feasible but not efficient. Note that the slope of the efficient frontier decreases as the variance of profit increases, implying a trade-off between profit and risk. Finally, the risk increases sharply as profit approaches the maximum profit.

[Insert Fig. 4 here]

Depending on the farmer's attitude to risk, the expected profit from a particular crop portfolio can be traded-off against risk along the efficient frontier. The marginal rate of substitution (MRS) between the mean and variance of profit is used to describe farmers' risk attitudes and is defined as follows (Kim and Santomero, 1988):

$$MRS = \frac{\Delta Mean}{\Delta Variance}. \tag{8}$$

For example, if the farmer believes that profit and risk are equally important then MRS=1, and the optimal mean-variance pair can be found as shown in Fig. 4. The optimal pair in this case, D, corresponds to mean=€ 8.18k and variance=€^{2}2.69k.

4.1.2 Static portfolio of crops

The crop portfolio is presented in the first instance in terms of individual crop areas (the percentage of the total arable area sown to each crop) and in the second, in terms of profits (the proportion of total profit attributable to each crop in the portfolio).

In figure 5 the optimal static portfolios of crop areas are shown for various levels of risk (i.e. variance in profits), and compared to the observed average areas for these crops for the region. We find that when the farmer's aim is to maximize expected profit in the short-run without regard to variance, they should only grow winter wheat, sugarbeets and rapeseed (i.e. the columns *max variance*). Barley is a bad choice in this case due to its poorer profitability. However, if the farmer is more cautious of risk —moving from *max variance* to ¾, to ½ to ¼ and finally near 0 of max variance in Fig. 5—they begin to grow grass and then also barley as insurance.

[Insert Fig. 5 here]

Grass fallow is a non-profitable but risk-free choice, while barley has different growing characteristics from other crops, e.g., a negative yield response to temperature (Table 5). When farmers do not care about risk, they should increase the proportion of winter wheat at the expense of barley and grass fallow. The areas of sugarbeet and rapeseed are mainly restricted by crop rotation constraints. The area allocated to sugarbeet is relatively small (≤ 15% of total area) while it constitutes a relatively large share of total profit (≥ 40% of total profit) (Fig. 6).

[Insert Fig. 6 here]

4.2 Dynamic results

In this section, we use the dynamic model to evaluate the combined effects of crop diversification and dynamic SOC management. The discount rate is set to 7% which is the rate used by farm consultants for evaluating farm investments in the region (AgriWise, 2011). Results for other discount rates (0%, 3% and 28% (Duquette *et al.*, 2012)) are also examined. It is found that the results are robust to the choice of discount rate.

4.2.1 Dynamic efficient frontier

In the dynamic model, the maximum profit of € 55.5k (accumulated over five years) is associated with a risk (variance) of €^{2} 263k. Similar to the static case, the slope of the efficient frontier decreases as the variance of profit increases (Fig. 7). Profit only decreases by around 30 percent while the risk decreases by 75 percent in the two models (Table 7).

[Insert Fig. 7 here]

[Insert Table 7 here]

4.2.2 Dynamic portfolio of crops

In the dynamic model, the farmer mitigates the total risk across the five periods through constructing crop portfolios and managing SOC. In contrast to the static model, the role of growing grass fallow includes investing in SOC for the future in addition to being a risk-free investment. Compared with the results of the static model the risk-reducing advantage of barley deteriorates in the dynamic context. Instead grass fallow becomes a relatively better option to reduce total risk (Fig. 8). Growing grass fallow increases SOC which boosts optimal yield and fertilizer use efficiency (yield per unit fertilizer) in the future (i.e. ecosystem services substitute for fertilizer input). It can also reduce farmer's dependence on the weather, since higher SOC is associated with, e.g. better water regulating capacity (de Vries *et al.*, 2012).

[Insert Fig. 8 here]

Conserving SOC in the last period appears uneconomical but this is purely a result of the terminal period as benefits beyond the last period are not considered in the model. Consequently, the area of grass that can be seen in Fig. 8 shows a decreasing trend, implying that farmers conserve SOC in early periods and use it to its maximum in the last period.

The profits in each of the five periods show an increasing trend (Fig. 9 where profit*i* stands for the profit in period *i*) meaning the farmer should conserve SOC for long term use even when considering positive time preferences. Furthermore, the ratios of profit1 to profit5 for the low risk tolerance are lower than those for the high risk tolerance: if farmers become more cautious, they should preserve greater productive potential (growing grass to conserve SOC) for future use.

[Insert Fig. 9 here]

4.2.3 Dynamic management strategies for soil organic carbon

To examine the effect of management strategies, the relevant indicators of SOC are examined for different levels of risk tolerance (Fig. 10 where Carbon*i* stands for the average SOC across all fields in period *i*). Farmers with high risk tolerance, use SOC at a higher rate than it is restored and hence average SOC declines (-0.008%/year for max variance) while farmers with a low risk tolerance should conserve SOC to reduce future risks.

[Insert Fig. 10 here]

From the perspective of the dynamics of the variation coefficient of SOC, p*i* (i.e. Standard deviation/Mean), we find a strong decreasing trend in the variation of SOC across fields (figure 11), which we refer to as a carbon *convergence* strategy: SOC content should be equalized across fields of identical soil type. In contrast to accepted ecological perception (Lal *et al.*, 2004), we find that conservation of carbon might not be the only way to increase profits and reduce risks in the future. Since fields with relatively high SOC content (*ceteris paribus*) have higher marginal productivity than fields with lower carbon content it is not economically efficient to adopt a uniform conservation strategy across fields. Rather farmers should have a targeted plan to produce less on fields with below average SOC to restore it and produce more on fields with above average SOC to deplete it, thereby reducing the variance of (or equalizing) SOC across fields. Our carbon convergence strategy reflects a standard economic principle: the Law of Equi-Marginal Utility (or Gossen's second law) (Nisticò, 2005). In our case, farmers should manage SOC to equalize its marginal productivity across all fields.

[Insert Fig. 11 here]

In summary, dynamic management of SOC can increase profit and (or) reduce risk in the future. For example, when risk is ignored in the max variance scenario in the dynamic context (Table 8), profit in the fifth period is € 13.7k which is 115% of profit in the static context; however, its variance also increases to €^{2} 16.9k or 134%. By contrast, for the ½ max variance goal in the dynamic context, profit and its variance in the fifth period is € 12.9k and €^{2} 10.2k, which amounts to 108% and 81% in the static context showing the positive effects of SOC management on profitability and reducing risk.

[Insert Table 8 here]

5. Concluding remarks

Conservation of natural capital is recognized as being important for sustainable development (Dasgupta, 2010), however, the focus has been on its economic value (Kareiva *et al.*, 2011) and not its role in reducing risk. As we know, this article is the first attempt to evaluate the potential of soil capital for controlling multiple risks in agriculture. We developed a novel framework to analyze farm risk exposure that can account for correlated risks (interdependent weather events or market prices) and future impacts of current cropping decisions on expected farm profit and associated risk. The first problem we solved by introducing Copula methods for modeling correlated risks. The second, by constructing a dynamic portfolio model that considers yield response to the stock of SOC and stochastic weather events.

The results demonstrate that crop diversification and management of SOC can increase expected farm profit and reduce agricultural risk in the future. Spatial diversification alone is found to reduce over 70% of total risk at the expense of 30% of expected profit, which might imply a 70-30 rule (Pareto, 1971; Wang *et al.*, 2010; Brynjolfsson *et al.*, 2011). In essence, the 70-30 rule describes the asymmetry between risk and revenue for crop production. It demonstrates that most risk can be avoided by constructing an efficient portfolio of crops (in this case diversifying production across four different crops).

The novelty of this research is however that we show that the current choice of crop portfolio through its effect on SOC content (soil capital) can both increase future expected profit and reduce associated risk. Profit potential is improved due to the complementary or synergistic effect of soil ecosystem services on fertilizer input.

Relative risk is mitigated by the ability of the soil to buffer adverse weather events (e.g., higher soil organic matter content has higher water holding capacity and hence can help crops withstand dry spells) and for ecosystem services to substitute for costly inputs (e.g., nutrients). We also find that carbon conservation is not the only key to managing soil capital efficiently. Farmers should also reduce the variance of SOC across fields to mitigate the risk given the same revenue. Active management of soil capital has therefore the potential to mitigate two of the most serious risks faced by farmers today—energy price shocks and climate change—in a cost-efficient way. The management of soil capital goes well beyond the traditional crop rotation scheme whose aim is primarily to prevent the spread of crop pests and diseases.

Our results also have policy implications. In many areas of Europe today, soil organic carbon is declining due to intensive farming. We believe there are two prime factors driving this development. First, farmers are not likely to be well informed of the capacity of soil capital to mitigate agricultural risks (as far as we know, we are the first to demonstrate this quantitatively), although they could know the effect of conserving soil capital on long-term productivity (Cary and Wilkinson, 1997). Second, farmers—like most people—tend to be myopic (e.g. they focus on current profit rather than long-term, risk-adjusted profits) and/or overly optimistic while ignoring the potential future risks (Kahneman and Lovallo, 1993). As such, there could be a need for government to provide farmers with additional incentives to conserve soil capital since it would have twin advantages for the future (and hence agricultural sustainability): increasing profits and reducing risks. Particularly, as shown in the results above, it would be desirable for society to encourage the restoration of land that has been previously degraded (i.e., has low soil organic carbon content) to equalize the stock of soil capital across (otherwise similar) fields. Although our results are for a single agricultural region (Scania) in Sweden it is typical of intensive arable farming in northern Europe, and the methods can be applied to other regions where data is available.

We recognize that we don't consider the full complexity of soil organism relationships with ecosystem services (Wall, 2004; Lavelle *et al.*, 2006; Dominati *et al.*, 2010; Robinson *et al.*, 2012), but use the stock of soil organic carbon (SOC) as an indicator of soil capital in a production function approach. In this sense the production function models the average effect on yield of all supporting soil ecosystem services related to SOC. We also realize that the depletion of soil capital could be difficult to be restored if depleted below some threshold, but we do not consider extreme conditions (e.g., soil erosion which is well covered in the literature). An elaborated function to describe the relationships between farmers' land-use behaviors and soil ecosystem services in more detail could be developed and integrated in the current modeling framework in the future when relevant knowledge is complete.

Another noteworthy issue is that in the paper we only consider grass fallow as the way to conserve or restore soil capital. However, in reality there are also other ways (e.g. inter-cropping, reduced tillage, addition of manure, etc.). The cost effectiveness of these options could be examined in the future using our approach. Finally we used a fixed discount rate in our optimizations. However, in the long-term, the farmers' risk attitude may change over time, which could also be an extension of our paper.

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Table 1 The five families of Copulas considered in the model selection

Family	C(u,v)	Range of θ
Normal	$N_\theta(\Phi^{-1}(u),\Phi^{-1}(v))$	[-1,1]
Student	$T_{\theta,\gamma}(T_\gamma^{-1}(u),T_\gamma^{-1}(v))$	[-1,1]
Clayton	$(u^{-\theta}+\mathrm{v}^{-\theta}-1)^{-1/\theta}$	$(0,\infty)$
Frank	$\theta^{-1}\ln\{1+(e^{\theta u}-1)(e^{\theta v}-1)/(e^{\theta}-1)\}$	$(-\infty,\infty)-\{0\}$
Gumbel	$\exp\left\{-(\lvert\ln u\rvert^{\theta}+\lvert\ln v\rvert^{\theta})^{1/\theta}\right\}$	$[1,\infty]$

Source: Gregoire et al. (2008).

Table 2 Model selection criteria for temperature and rainfall Copula models (April)

Criterion	Model				
	Normal	Student	Clayton	Frank	Gumbel
Log-likelihood	3.05	4.11	-0.0007	-0.0002	-1.86
AIC	-6.06	-8.15	0.042	0.041	3.75
BIC	-6.02	-8.07	0.081	0.08	3.79

Table 3 Model selection criteria for price series Copula models

Criterion	Model				
	Normal	Student	Clayton	Frank	Gumbel
log-likelihood	-334.7	2.59	0.0001	-0.01	-33.24
AIC	669.45	-5.07	-0.0002	0.07	66.53
BIC	669.49	-4.99	-0.0002	0.1122	66.58

Table 4. The growth characteristics of crops as affected by weather variables

Crop	Sown[a]	Harvest[a]	Critical rain period[c] (month #)	Critical temperature period[c] (month #)
Winter Wheat	Sep(-1)[b]	Aug	4,5,6,7	9(-1),10(-1),…,8
Spring Barley	Mar-Apr	Jul-Aug	4,5,6,7	3,4,5,6,7
Sugarbeets	Apr-May	Oct-Nov	4,5,6,7,8	5,6,7,8
Winter Rapeseed	Aug(-1)	Jul	4,5,6,7	9(-1),10(-1),…,8

Source: a) Hammar (1990) which is a standard reference for crop production in Sweden; b) -1 denotes month in year prior to harvest; c) based on Hammar (1990) and expert consultation.

Table 5. Estimated parameters and their T statistics of yield response functions for four crops

Parameter	Winter Wheat	Spring Barley	Sugarbeet	Rapeseed
a_1	-148612.7	-76860	-709626.8	-54551
	(-127.51)	(-75.37)	(-50.71)	(-25.29)
a_2	43.56	54.09	60.48	10.51
	(13.65)	(11.45)	(3.22)	(2.74)
a_3	-0.13	-0.25	n.a.	-0.03
	(-8.42)	(-6.5)		(-4.73)
a_4	5382	4496	107230.4	6051
	(5.53)	(5.06)	(8.54)	(3.87)
a_5	-865.57	-722	-13448.53	-954.872
	(-4.44)	(-4.17)	(-5.46)	(-3.54)
a_6	-4.38	-5.1	-17.77	n.a.
	(-4.05)	(-3.32)	(-1.88)	
a_7	18.7	21.12	208.49	4.66
	(7.01)	(3.85)	(2.8)	(2.32)
a_8	-0.066	-0.07	-0.77	-0.03
	(-11.11)	(-3.57)	(-3.02)	(-2.57)
a_9	147	-304	714.28	-154
	(4.38)	(-8.53)	(2.18)	(-5.38)
a_{10}	72.03	37.75	291.627	25.32

	(18.2)	(14.96)	(8.58)	(10.54)
$\bar{R}^2$	0.97	0.97	0.91	0.53

Note: Estimated parameters in the table are all statistically significant at 5 % level. The numbers in the brackets are t statistics. a_1 is the parameter of the intercept term; a_2 is the parameter of the linear term of nitrogen; a_3 is the parameter of the quadratic term of nitrogen; a_4 is the parameter of the linear term of SOC; a_5 is the parameter of the quadratic term of SOC; a_6 is the parameter of the interaction term of nitrogen and SOC; a_7 is the parameter of the linear term of precipitation; a_8 is the parameter of the quadratic term of precipitation; a_9 is the parameter of the linear term of temperature; a_{10} is the parameter of the year.

Table 6. Normal crop rotation constraints for the region

Crop	Maximum percentage of total area	Frequency on plot
Wheat	75%	3 times in 4 years
Barley	75%	3 times in 4 years
Rapeseed	20%	1 time in 5 years
Sugarbeet	14.3%	Approx. 1 time in 7 years

Note: Data source is Hammar (1990).

Table 7. Comparison of total profits under different levels of risk (% of max profit)

	Max risk	¾ of Max Risk	½ of Max Risk	¼ of Max Risk	0% of Max Risk
Static model	100%	97.4%	89.8%	72.6%	0%
Dynamic model	100%	97.3%	89.1%	71.7%	0%

Table 8. Effects on profitability and risk-reduction of soil organic carbon management

Model	Static	Dynamic									
Levels of risk	Max risk	near 0% of max risk		¼ max risk		½ max risk		¾ max risk		max risk	
		a(K)	b(%)	a(K)	b(%)	a(K)	b(%)	a(K)	b(%)	a(K)	b(%)
Mean(€)	11.9	5.96	49.9	11.5	96.4	12.9	107.8	13.7	115	13.7	115
Variance (€^{2})	12.5	1.81	14.5	6.8	54.2	10.2	81	15.4	123.1	16.9	134.4

Note: *a* stands for absolute amount. *b* stands for percentage of the corresponding static result