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ARTICLE

Adoption of Regenerative Farming Practices in Agriculture: A Real Option Analysis

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ABSTRACT

We apply a real option analysis to the investment decision of US corn farmers to switch from conventional farming to regenerative farming under a carbon credit system. We establish the existence of significant "wait and see" effects that form a barrier for adoption of regenerative farming practices among farmers. Depending on assumed volatility levels, carbon credit price levels required to incentivize farmers sufficiently to consider switching practices can be twice as high than a traditional cost-benefit analysis would suggest. Farms with more corn acreage experience lower price thresholds to adopt regenerative farming than smaller farms. Finally, we show how individual practice changes such as the degree of nitrogen fertilizer reduction impact the propensity to switch.

Keywords: Regenerative Farming; Carbon Credits; Real Options

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1. Introduction

In 2022, globally almost 54 billion tons of CO2 equivalents (CO2e) (To add up all the different greenhouse gases, i.e., carbon dioxide, methane, nitrous oxide, and smaller trace gases such as hydrofluorocarbons and sulfur hexafluoride, into one number, they are expressed in CO2 equivalents (CO2e).) was emitted into the atmosphere as a consequence of human economic activity [1], causing rapid global warming. With the Paris Climate Agreement, the world community has committed to significantly limit the greenhouse gas emissions across all sectors of the economy. These global emissions must reach net-zero in 2050.

One sector that has a particularly large environmental impact is the food and agricultural industry. Agricultural production by itself is responsible for 11–15% of all human emissions, and if the impact of land-use change, deforestation, and broader emissions within the food supply chain are taken into account, this number rises to roughly 50% [2]. About 60% of the total global emissions of almost 54 billion tons of CO2e mentioned above remains in the atmosphere. About 40% can be absorbed back by earth, by soils, trees and oceans. So, on the one hand agriculture emits a lot of greenhouse gases. But on the other hand, farmers' land and trees have the unique capacity to take them out of the atmosphere again. It is therefore important, first and foremost, to avoid and reduce these emissions. At the same time, removing these greenhouse gasses from our atmosphere is every bit as important. As long as there are high levels of these gasses in the atmosphere, the earth will continue to warm, no matter how much we reduce emissions. So, all sectors need to work both on the reduction and removal of carbon emissions.

The agricultural sector can play a key role in the removal of greenhouse gases from the atmosphere because agricultural crops can capture CO2 and bind this in the form of carbon into the soil. Carbon sequestration takes place when regenerative production techniques are applied. Conventional production of food has impacted the planet's soils, reducing the natural carbon content of cultivated soils by up to 70% [3]. Rising temperatures, combined with drought and floods, exacerbate this soil degradation and erosion. This has led to severe biodiversity degradation, which poses a threat to food security [4].

Only healthy soil has the ability to absorb carbon from the atmosphere. Regenerative practices like reducing tillage, using cover crops, implementing crop rotation schemes, limiting the use of fertilizers and pesticides can contribute to improving carbon sequestration processes (ibidem). In this way regenerative agriculture is a form of producing food that strengthens rather than depletes the soil. By disturbing the natural processes in the soil as little as possible, soil health increases and the soil can sequester more carbon. It also improves water balance, biodiversity and nutritional value of food. However, switching to regenerative farming is costly for the farmer [5]. This is due to the fact that the negative environmental and climate impacts of conventional farming are not priced, while the deployment of regenerative practices may incur additional costs.

One of the fundamental problems in the food system is that the cost of greenhouse gas emissions, nitrogen deposition, water usage, loss of biodiversity, chemical pollution and depletion of soils is not adequately priced. Globally, we do not pay these external cost of food production. The benefits that come from these ecosystem services — such as biodiversity, better water management and pest control — are freely available for all, whereas farmers pay for them on their own. New business models are needed for farmers and landowners that include compensation and reward schemes for ecosystem services [6]. Without these models, farmers will not invest sufficiently in more sustainable practices as long as they cannot pass on the extra costs to players down the supply chain, including food processors, retailers and consumers. These parties are currently not willing to pay more for sustainably produced food. Yet, many governments and food and other corporates have committed to the Paris Accords and have set pathways to net-zero emissions accordingly. Meeting those commitments requires reducing the externalities of food production.

Carbon sequestration in soils is a potential income source for farmers through the use of verifiable and creditable carbon markets that allow farmers to benefit from sustainable practices [7]. The voluntary carbon market can play an essential role in internalizing those effects, as it facilitates the inflow of money from downstream supply chain partners and actors in non-food supply chains who buy carbon credits from farmers.

A carbon credit that is sold on this market represents one ton of CO2e reduced or removed per hectare. Generated and certified carbon credits are subsequently sold to parties that would like to offset their carbon footprint. The price per credit unit constitutes an explicit subsidy for emission free production, such that a new revenue stream is introduced for the farmer. So generating carbon credits is not an end in itself but a means of putting a price tag on ecosystem services provided by farmers.

The economic incentives that farmers face under a carbon credit mechanism are shaped by both carbon credit price levels and market volatility [8, 9]. A carbon credit mechanism will only significantly impact farmer behavior when carbon credit prices are sufficiently high to cover the net additional costs of carbon sequestration practices. Carbon credit prices must be sufficiently high not only to overcome any investment costs or adjustment costs related to switching to regenerative farming, but also to address behavioral problems (moral hazard, adverse selection) which require costly monitoring approaches. Given the different costs of proposed practices, the potential for global sequestered carbon has been estimated to range between 400 to 1200 million tons per year, depending on where carbon prices range between \$20–\$100 [2, 10]. Furthermore, carbon credit prices must all stay consistently at a high enough level to form an attractive long-term investment prospect. Under high market volatility farmers will face greater uncertainty about the stability of future inflows from carbon credits and therefore provide disincentives to adopt regenerative practices.

Voluntary carbon markets are relatively new and have not fully matured [11], carbon credit price volatility can be significant as a consequence. Unlike the compliance market, the voluntary nature of demand implies that the perceived quality of credits plays a considerable role in the price that that buyers of credits are willing to pay [12, 13]. This perception can change rapidly depending on e.g., stricter self-regulation set up by NGOs like the Integrity Council for the Voluntary Carbon market, or by negative media attention when low integrity credits enter the market. The large variety in the types of projects that generate nature based carbon credits also make it difficult for buyers to discern differences in the quality between projects. That is why certification standards are set by independent verification organizations, and credits can be verified accordingly. Still, when some project goes bad, this may influence the larger overall demand for other projects as well, even when project success is unrelated. Furthermore, voluntary carbon markets derive their relevance from an absence of formal regulation or government policy. New legislation by governments, e.g., the expansions of compliance markets or the introduction of carbon taxes, would influence demand for voluntary carbon credits and generates further uncertainty.

Overall, when farmers contemplate switching to regenerative farming, the decision-making process is characterized by (partially) unrecoverable investment costs and considerable uncertainty surrounding future revenue flows from generated credits. At the same time, there is scope to delay the switching decision to later crop years. Under these conditions, farmers may adopt a ‘wait and see’ attitude. This inertia is not well described by classical investment theory that relies on the net present value rule to capture investment behavior. Real option analysis is frequently proposed as an alternative technique that is tailored to decision making problems under uncertainty and irreversibility [14].

Real option theory describes how investment opportunities that can be postponed and are costly to reverse can be modeled as an investment option, i.e. the holder of the option has the possibility, but not the obligation to initiate the investment at any point in time. This option has an inherent value as it protects against negative market outcomes, therefore exercising it creates an opportunity cost. Real option analysis postulates that this opportunity cost should be incorporated in the cost benefit analysis for the investment decision. It then presents the ultimate investment decision in terms of a price threshold, such that when the so-called state variable (e.g., a dynamically evolving carbon credit price) passes this threshold, the investment should be carried out[14].

Real option methodology has been used to explain observed investment decision making in a broad variety of settings within the agricultural industry. Purvis et al. pioneered with the application of real option methodology to agricultural investment problems[15]. Their study delves into the analysis of technology adoption in free-stall dairy housing stressing the effects of uncertainty and irreversibility. They quantify how these factors increase investment thresholds for farmers and emphasize the implications of these findings for the formulation of environmental regulation related to agricultural practices. Winter-Nelson and Amegbeto use real option analysis to research the impact of increased agricultural price variability due to commodity market liberalization on soil and water conversation[16]. They apply their methodology to the case of terrace construction in Kenia and find that the impact of greater price variability can more than offset the incentivizing effects of higher commodity price levels. In a study conducted by Odening et al., real option theory is employed to model investment behavior in hog production[17]. They conclude that the value of waiting can drive investment triggers significantly above levels predicted by classical investment theory. Seo et al. use a real option approach to analyze the adoption of irrigation technology among farmers in the Texas High Plains[18]. Their simulation results highlight inertia among farmers when deciding on replacing existing irrigation systems for new systems with better water application efficiency. As a final example, Sanderson et al. use real options to analyze the adaptation of Australian wheat production to climate change[19]. They derive threshold values for transitioning to different production regimes to showcase how farmers would operate when a series of options are presented to them.

In general real options have been established to explain investment decisions by farmers better than the net present value method, and usage of real option theory for agricultural investment problems is still underutilized[20, 21]. In this paper we therefore use a real option approach to explore what carbon credit price levels are required to incentivize farmers to consider switching to regenerative farming. To the knowledge of the authors, this paper is the first to apply a real option approach to analyze the economic viability of carbon markets for carbon sequestration in agriculture. The adopted technique allows us to present the ultimate switching decision in terms of a clear threshold value, i.e. an investment trigger, such that when stochastically evolving carbon credit prices pass this threshold, the decision to switch practices should be carried out. We subsequently compare investment triggers under real option and net present value methodologies to assess the effect of assumed investment rules on required carbon credit levels for intervention adoption. For effective climate and nature policy, it is imperative that policymakers better understand how uncertainty affects farmers' investment behavior and to predict this behavior in the future. Governments, NGOs and corporates can then better shape (self)regulation, subsidization and purchasing decisions in the voluntary carbon market so that farmers are encouraged to adopt regenerative farming.

Additionally, our developed modeling approach allows for more detailed analysis on how market conditions and micro-economic variables shape farmers' incentives to switch to regenerative farming practices under a carbon credit framework. The model can therefore be used by policymakers to find out how the carbon credit price levels required to stimulate regenerative farming depend on the broader decision-making environment. Having a good understanding of under what conditions carbon credits can be a successful mechanism to stimulate regenerative farming practices is paramount to estimating the future relevance of sequestration-based carbon credits in contributing to mitigating the global heating problem as well as the restoration of biodiversity and better water resilience.

Besides research that aims to explain farmer behavior, real option methodology has also been used to provide normative frameworks on how farmers should invest or make decisions. For instance, Hertzler uses real options to design decision making diagrams for climate change adaptation[22]. He applies these frameworks to climate adaptation decisions with respect to grazing and dryland cropping. Additionally, he uses real options to model climate risk sharing opportunities for farmers such as yield insurance. These examples illustrate how real option models can serve as a practical decision-making tool under uncertainty. When provided with the right calibration data the model developed in this paper can be used in a similar vain.

The remainder of this paper is organized as follows. Section 2 covers materials and methods, containing details on the model design, the solution algorithm and model calibration. Next, simulation results are presented in section 3 and discussed in section 4, including comments on the limits of our research. Finally, section 5 concludes and provides policy implications. Appendix A and B contain further information about the parameter values used in the model and a sensitivity analysis concerning various model assumptions, respectively.

2. Materials and Methods

We build a real option framework in order to model farmers' behavior given the investment problem of moving away from conventional farming practices towards regenerative farming practices. As the decision maker we take the viewpoint of a representative farmer (i.e. typical or average farmer), from this point onwards simply referred to as the farmer. We assume this farmer has the opportunity, but not the obligation, to switch practices once every year up to an assumed time horizon of $T \in Z$ years. If the farmer has not adopted regenerative farming after this period, conventional practices will be applied indefinitely. Also, if the farmer does switch to regenerative farming before T, we assume no option exists to switch back towards conventional practices. Once regenerative farming has been adopted, the farmer will continue to apply these practices indefinitely. We indicate the state of the farm operations by the binary indicator *s*, where a value of 0 indicates conventional practices, and a value of 1 regenerative practices.

Within the setting of our model stochastically evolving carbon credit prices will form the source of uncertainty during the decision-making process of farmers. Define $S(t)$ as the carbon credit price level, where $t \in Z$ denotes the time period. Because carbon credit prices are indicative of the relative profitability of the regenerative farming state, we also refer to $S(t)$ as the state variable. We assume the behavior of the carbon credit prices process is described by a geometric Brownian motion. Let μ indicate the drift rate, determining the expected growth of the process over time. We capture the variability of the process by the volatility parameter σ. If we subsequently set $dz(t)$ as the increment of a Wiener process, we have:

$$dS(t) \ = \ \mu S(t)\, dt \ + \ \sigma S(t)\, dz(t) \qquad (1)$$

Under the above condition carbon credit prices will develop as a random walk with a trend, which we believe adequately describes voluntary carbon credit price dynamics in practice. In particular we don't have any evidence that more complex mean-reverting processes or jump processes would describe price movements better. For more background on the definition and characteristics of a geometric Brownian motion we refer to Dixit and Pindyck [14].

We assume the goal of the farmer is to maximize the value of the farm, which consists of the discounted stream of future profit flows. Denote the profit flow during any year t by π_t. Profits are subsequently determined by the difference between revenues and costs.

Let $t_s$denote the moment at which the farmer switches practices. During $t < t_s$ revenues consist of the income derived from crop production. Three factors contribute to these revenues. First there is the exogenously determined price $P(t)$ the farmer receives per unit from crop sales. Second the total area of cropland *A*, which we assume to remain constant over time, partly determines overall production levels. Finally, crop yields $y(s,t)$ determine production per area of cropland. In reality crop yields are related to a great many variables, some influenced by the farmer like adopted farming practices, others outside the farmer's control like weather patterns. Our aim is not to endogenously model the effect of these variables on crop yields, this remains outside the scope of this paper. Instead, we require the crop yield to be exogenously specified. To allow for flexibility in this specification we allow for different crop yields over time and per policy state. This way we allow for different assumptions on how regenerative farming affects crop yields in the short-term and long-term and check how these scenarios affect farming decision making. Total yearly revenues from crop production are now $P(t)\, Ay(s,t)$.

During the period $t \geq t_S$ the farmer also receives income from carbon credits: the farmer receives a price $S(t)$ per credit from carbon credit sales. This revenue stream is not indefinite as there are physical limits on the build up of soil carbon and term limits on carbon credits production contracts. We assume the carbon credit revenue stream ends after a period of $\bar{T}$. Define the yearly change in carbon stock per acres/hectare $\delta(s,t)$ subsequently as follows:

$$\delta(s,t) = \begin{cases} 0 & \text{if } s = 0 \text{ or } t - t_s \geq \bar{T} \\ \bar{\delta} & \text{otherwise} \end{cases} \quad (2)$$

Here $\bar{\delta}$ is a fixed parameter that indicates the average yearly carbon build up in the soil between t_s and $t_s + \bar{T}$. In practice this difference may be variable over time, but this would require a more elaborate modeling of biochemical processes. In total carbon credit revenues are now $S(t)\,A\delta(s,t)$.

On the costs side of farm operations, we adopt the simplifying assumption that all costs are deterministic and exogenously provided. Farmer costs originate from a broad range of inputs/factors like seeds, fertilizer, chemicals, fuel, lube and electricity, repairs, purchased irrigation water, hired labor, depreciation of equipment, opportunity costs of land, and general farm overhead. We assume input quantities scale with farm size A. Without loss of generality, let $q(s)$ be an array containing the input quantities per acre for any relevant costs incurred during farm operations. Usage of any kind of inputs may depend on the state *s*, for instance farmers may reduce fertilizer usage as part of the switch to regenerative farming. If we subsequently let $c(t)$ be an array of associated costs per unit of input type, then total input costs are now calculated as $c(t)^T Aq(s)$.

Above we have made simplifying assumptions with respect to the crop price $P(t)$ and input costs like fertilizer prices by not modelling these variables stochastically. In reality these and other input prices can be highly variable and have a major impact on farm profitability. Furthermore, when the state has an impact on crop yields and input usage the farmer may naturally want to take variability in these factors into account during the decision making process of switching to regenerative farming. However, introducing stochastic processes for these variables would significantly increase model complexity as well. In order to attain more easily interpretable results, we choose not to work with multiple state variables and leave this out of scope for this paper. It may be adopted as a topic for future research.

Indicate yearly profit flows by $\pi(s,t)$. These profits depend on the state of the farm and the time period, they can be described as follows:

$$\pi(s,t) = P(t)\,Ay(s,t) + S(t)\,A\delta(s,t) - c(t)\,TAq(s) \quad (3)$$

We assume all profit flows are earned by the end of the year, i.e. profit flows have to be discounted in order to find their value at the start of the year.

Part of the investment problem are friction costs I incurred during the process of switching states. We assume I is fixed and does not change over time. Friction costs consist primarily of investments in newly required equipment.

Next let *r* denote the discount rate. Just like friction costs we assume this factor is fixed and does not change over time. The time preferences of the farmer are indicated by the discount rate: a forward-looking farmer has a low value for r, whereas a farmer that is focused on the short-term has a high r. We require $r > \mu$, if this condition is violated the expected growth rate of carbon credit prices is larger than (or equal to) the discount rate. In that case it becomes optimal to never switch practices and wait indefinitely as the discounted expected returns of waiting will always be positive.

Under the above assumptions, we can now describe the value of the farm $V(t)$. First note that in case the farmer chooses to use conventional farming practices for the next year, the value of the farm at any year $t < T$ is simply the discounted expected value of the farm next year plus the yearly profit flow.

$$\frac{\pi(0,t) + \mathbb{E}[V(t+1)]}{1+r}$$

We have assumed that the last moment the farmer can switch farming practices is at the decision horizon T. If the farmer has decided not to switch practices before this moment, not switching at time T either would lock in the farmer into conventional farming practices indefinitely. In this case, the value of the farm will be given by the sum of all discounted future profit flows. Because there is no stochasticity involved here, this value is known at T with full certainty:

$$\sum_{i=1}^{\infty} \frac{\pi(0,T)}{(1+r)^i}$$

When the farmer switches to regenerative farming practices, switching back is not possible by assumption. Therefore the farmer will continue to receive the regenerative farming profit flow indefinitely. The value of the farm in this case is the sum of all discounted future profit flows minus the investment costs of switching:

$$\mathbb{E}\left[\sum_{i=1}^{\infty} \frac{\pi(1,t)}{(1+r)^i}\right] - I$$

Because the farmer has a choice between two sets of practices, the value of the farm is dependent on the farmer's behavior. To resolve this dependency we employ the earlier assumption that at any decision moment t the farmer chooses optimally, i.e. with the goal of maximizing farm value $V(t)$. This allows us to define the farm value as follows, a condition also known as the Bellman equation [14]:

$$V(t) = \begin{cases} \max\left\{\frac{\pi(0,t)+\mathbb{E}[V(t+1)]}{1+r}, \mathbb{E}\left[\sum_{i=1}^{\infty} \frac{\pi(1,t)}{(1+r)^i}\right] - I\right\}, \; if\, t < T \\ \max\left\{\sum_{i=1}^{\infty} \frac{\pi(0,t)}{(1+r)^i}, \mathbb{E}\left[\sum_{i=1}^{\infty} \frac{\pi(1,t)}{(1+r)^i}\right] - I\right\}, \quad if\, t = T \end{cases} \tag{4}$$

Assume the first opportunity for the farmer to switch is at $t = 1$. The aim of the farmer is to find the optimal switching moment $t_s \in Z : t_s \in [1, T]$.

In order to solve our model we use the Longstaff-Schwartz algorithm, a widely used numerical method used for pricing American-style options [23]. One reason behind the popularity of the Longstaff-Schwartz method is its flexibility, as it can be applied to a wide variety of problem settings. As such, the algorithm has been used in a broad range of applications, including pricing options on stocks, bonds, futures, and commodities and also in real options. The Longstaff-Schwartz algorithm, while powerful and widely used, does have some limitations such as potential look-ahead bias [24], and the key innovation of this method in using least squares regression to estimate the conditional expected payoff for continuing to hold the option, similar to any estimation process, can introduce errors. Furthermore, the simulation-based nature of the algorithm may lead to increased computational complexity as the number of state variables grows. But, despite these challenges, in the absence of closed form solution for American option valuation, this algorithm can generate accurate results whilst having a greater computational efficiency than alternative numerical methods like the finite difference and binomial tree methods [25]. These attributes lead us to adopt it and apply it to the optimization problem (4).

Following the Longstaff-Schwartz algorithm, we first simulate a number of *n* paths of T steps for the carbon credit price $S(t)$ according to the the process (1), as depicted by **Figure 1** below. These price paths reflect alternative realizations of future carbon credit price dynamics, collectively they give an idea of the uncertainty inherent in carbon credit prices. The generated paths will form the basis for estimating continuation values, i.e. assessing what the value of the option will be tomorrow if we don't exercise it today.

We analyze these paths via backward induction. Starting at the endpoints, for each individual path we can observe $S(T)$ and calculate $V(T)$ according to (4). Next, we recursively apply equation (4), where for each period we need to determine whether it is optimal to exercise the option (i.e. switch to regenerative farming) or to continue and keep the option alive (i.e. staying with conventional farming).

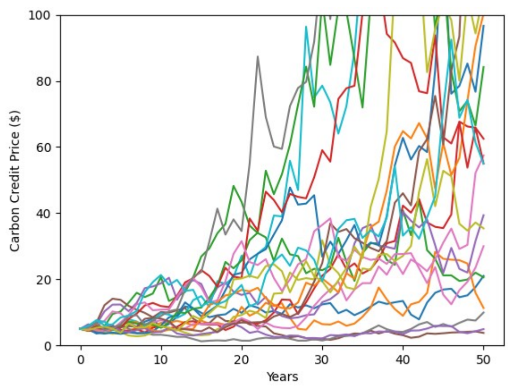


Figure 1. Twenty example realizations of carbon credit price paths simulated on the basis of the stochastic differential Equation (1).

To do so we require the value of $E[V(t+1)]$ for each remaining time period. These expected values are estimated by running linear regressions using the simulated paths as input data. The dependent variable Y for these linear regressions is the realized discounted cash flow of the next period to model for $V\,(t+1)$. The independent variables are polynomial transformations (following Longstaff and Schwartz[23]) of the current state $S\,(t)$. If we denote $S\,(t)$ by X and use a second-degree polynomial then we obtain the regression function below where the regression parameters β_0, β_1 and β_2 have to be estimated:

$$\mathbb{E}\,[Y|\,X] \;=\; \beta_0 + \;\beta_1 X \;+\; \beta_2 X^2$$

Each path forms a combination of data points, where only paths that are currently "in the money" (in the context of the put option that Longstaff and Schwartz value) are taken into account for running the regressions[23]. This selection is made to achieve better estimation results.

We have adjusted the Longstaff-Schwartz method from its original application to American style put options to function as a solution algorithm for our present real option model. To do so we have applied the following adjustments to the algorithm:

- Unlike the put options analyzed by Longstaff and Schwartz[23], not exercising our real option still leads to cash flows, i.e. the profits earned under conventional farming. This means that for calculating cash flows we cannot only look at exercise values, but we should also take any cash flows under continuation into account. This is relevant when establishing $V\,(T)$ at the start of the procedure, as this value will deviate from 0 even when the option is never exercised. Furthermore, the cash flow matrix that needs to be recursively updated during the procedure is no longer sparse due to the profit flows $\pi(0,t)$ that are earned in case of continuation. All these cash flows for all upcoming periods need to be discounted accurately when establishing the dependent variable for the linear regressions.
- The equivalent of being "in the money" in the present real option setting is that the immediate exercise value is larger than the series of discounted infinite cash flows received when conducting conventional farming indefinitely.

For any particular set of model parameter values (including the originally selected value for $S\,(0)$) we can determine the percentage of paths where investment has been triggered before the time horizon T has passed. This is displayed in the upper part of **Figure 2.** A higher percentage signals a higher likelihood that the representative farmer will adopt regenerative farming practices. Furthermore, we can obtain the distribution of stopping times across all paths from the simulation output, see the lower part of **Figure 2.** This gives an indication of how quickly the representative farmer is willing to switch practices. Both of these measures are directly dependent on the value adopted for the time horizon T. That is, a longer time horizon may cause more farmers to invest because there are more opportunities to do so. This would also change the stopping time distribution.

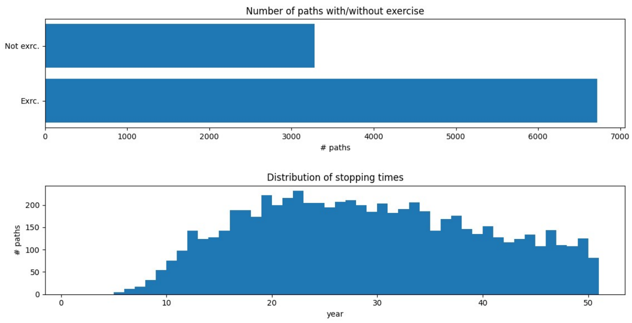


Figure 2. The amount of paths that exercise/do not exercise the investment option (upper graph) and the distribution of exercise times (lower graph) of an example simulation run.

From the simulation process we are able to derive an optimal trigger level, which is defined as the carbon credit price threshold level at which upon the first passing of the dynamic price process it is optimal to invest. This trigger level is the key variable of interest, it signals for a given set of parameter values what level carbon credit prices should reach in order to incentives farmers sufficiently to switch to regenerative farming from a real option perspective. In case the model has been calibrated for any individual farmer the trigger level can function as a normative result, it signals the optimal price level at which the farmer should adopt regenerative farming practices. If instead the model has been calibrated for an "average" farmer it provides a descriptive result from an economic perspective by indicating what carbon credit price level can be considered the tipping point for large scale adoption of regenerative farming.

We derive the optimal trigger level by letting $S\,(0)$ deviate from its selected value and instead running the algorithm for a series of monotonic increasing initial states $S(0)$ while keeping the seed constant. Meanwhile we compare the predicted option values with the net present value of switching practices at the first possible opportunity. Presuming the first $S(0)$ value is sufficiently low, the net present value and option values should converge, until they coincide, see also **Figure 3**. This is the point where the Longstaff-Schwartz algorithm predicts immediate exercise for all simulation paths. We take the smallest $S(0)$ value for which this holds true as the optimal investment trigger level. Note that because we are searching for the point of immediate invest, the trigger level is not affected by the selected value for time horizon T.

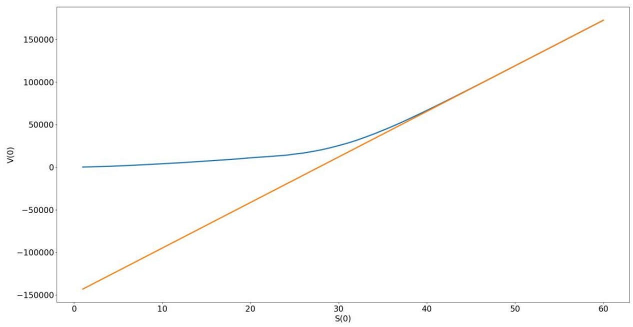


Figure 3. The investment value according to the net present value methodology (including the opportunity costs of foregoing conventional farming indefinitely) assuming immediate investment (orange) versus the real option methodology (blue) as a function of .

To illustrate the functioning of the model we will further specify a representative farmer. We presume this farmer is active in Iowa and only farms corn. We adopt a 50-year investment horizon, with one opportunity to switch practices every year. We take 2023 as the starting year for our simulations. The calibration process is largely based on simulation results from the COMET farm model for biochemical parameters and USDA survey data for economic parameters, any remaining missing values are set by assumption.

As a first step we need to define the set of practices the farmer can choose between, i.e. what is the definition of the state *s* and how does this state affect the profit flows $\pi(s,t)$? We base our definition of the management practices per policy state on the "VM0042 Methodology for Improved Agricultural Land Management" published by Verra, a nonprofit organization that is one of the most well-known names in the setting of standards for carbon markets.

In order to calculate the yield of carbon credits over time on the basis of farm management practices we use the COMET farm model. This is a biochemical model developed by NREL and Colorado State University. On the basis of farm management practice data the model calculates for a given field among others the yearly amount of emissions and change in the carbon stock in the soil. By comparing the model outcomes for a set of management practices before the intervention to the situation after the intervention, the parameters $\bar{T}$ and $\bar{\delta}$ can be established. From this we can calculate the amount of carbon credits generated during the intervention period.

The COMET farm model tracks and provides output on soil carbon accumulation, as well as carbon dioxide, nitrous oxide and methane emissions. Not all sources of emission are taken into account, e.g. for instance fossil fuel emissions related to the use of farming equipment is not reported on by the COMET model. For our purposes, the variables that the COMET reports on form a subset of the factors that can contribute to the generation of carbon credits under the VM0042 methodology. For instance reduction in fossil fuel emissions can contribute under VM0042. Our estimates $\bar{\delta}$ will therefore be on the conservative side. We denote $\delta(s,t)$ in metric tons of CO_2e per acre, i.e. the carbon and emission flows are transformed in terms of CO_2e.

The VM0042 methodology lists a number of farming practices that can be part of regenerative farming program with the aim of generating carbon credits. One important precondition is additionality, i.e. practices should only be adopted as a result of the incentives provided by carbon credit revenues and should not have been implemented anyhow. The listed practices under VM0042 include, but are not limited to, reducing the tillage intensity, the introduction of cover crops and limiting nitrogen fertilizer application.

The rationale behind the mentioned practice changes is as follows: heavy tillage disturbs the soil, allowing stored soil carbon to escape, whereas zero tillage allows the soil to absorb more carbon [26]. The same positive relationship between farming practice and degree of carbon sequestration applies to planting cover crops.

It reduces soil erosion and improves soil health because the roots and shoots of cover crops feed bacteria, fungi, and other soil organisms [27]. Furthermore, by improving soil health via e.g. cover cropping, regenerative farming allows for reducing the reliance on synthetic sources of soil nutrients like nitrogen fertilizer. However, the effect of nitrogen fertilizer usage on CO_2e emissions can be complex. Applying nitrogen fertilizer causes N_2O emissions, which directly contribute to CO_2e. However nitrogen fertilizer usage also has a positive impact on carbon sequestration rates, because it helps to increase biomass production and it improves carbon-nitrogen (C:N) ratios of residues returned to the field [28]. The net impact on CO_2e emissions may be situation dependent, but the high input costs provide farmers with additional incentives to reduce the usage of nitrogen fertilizer, especially when there are limited long-term effects on yield.

We will consider changes in these three farming practices as the differentiating factors between the two policy states *s*. By doing so we are assuming that none of these changes have been adopted by the farmer in the initial state, as required by the additionality principle. In practice 32,53% of farmers in the heartland region already switched to no-till farming by 2017, whereas 4,63% used cover cropping [9]. Our modelling scenario will therefore only reflect the situation of farmers that have not yet made these switches.

The COMET model has input fields related to each of these three practices, such that the effect of the policy change can be simulated. **Table A1** in **Appendix A** summarizes the parameter values that have been selected to run the COMET model for the base scenario.

To calibrate $\bar{T}$ we can perform COMET runs to gauge how long the accumulation of soil carbon and generation of carbon credits will continue under regenerative farming practices. The simulation outcomes show that the accumulation of soil carbon will continue for at least 50 years. The contracts farmers enter into typically don't last that long, so to stay on the conservative side we have set $\bar{T}$ = 30. **Appendix B** provides a sensitivity analysis on the impact of different assumptions for $\bar{T}$, see **Figure A1**.

Data related to farm costs and returns can be gathered from the United States Department of Agriculture (USDA). Since 1975 the USDA estimates the annual costs and returns of major agricultural commodities based on periodical surveys conducted among farmers. We use the 2022 data for the heartland region. The estimates are provided as a detailed breakdown of (among others) farm costs for several US regions, denoted as dollars per planted acre. **Table A2** in **Appendix A** provides more details about the adopted cost parameters. Each individual cost parameter forms a separate entry in the array $c\,(t)$.

The USDA survey does not list seed costs separately for cash crops and cover crops. As such, we make the simplifying assumption that the listed seed costs are for cash crops only, and that upon the introduction of cover crops these costs rise by a fixed percentage, see **Appendix A**.

In order to determine the investment costs I we need to establish the costs of new equipment (e.g. a no-till drill). In practice the costs of required machinery depend on a variety of factors. First of all, what machinery does the farmer already possess that could be adapted for usage under regenerative farming practices? In case new equipment is indeed required, is it acquired or leased? And in case it is acquired, is it new or second-hand? Based on list prices of farm equipment and estimations derived from conversations with agronomists we will adopt a value of \$100.000 as our baseline value. A sensitivity analysis for I is subsequently included in **Appendix B**, see **Figure A1**.

On the side of farm revenues, we require input on $P\,(t)$. An analysis of historic price dynamics shows that corn prices exhibit mean-reverting behavior around a long-run average, lacking a clear trend for extended periods [29]. Therefore, we simplify our analysis by assuming that the corn price $P(t)$ stays fixed over time. As a baseline we take the 2022 corn price from the USDA survey.

A further component of farm returns are the expected yields $y(s,t)$. The COMET farm model does not calculate yields, instead it requires it as an input variable. Therefore, we adopt the reported value from the USDA survey as a base value, which equates 200 bushels per acre. We apply this value by default when the farm operates under conventional farming practices ($s = 0$).

To model any potential effect of changing management practices on cash crop yields we follow results from the agronomic literature. However results can conflict and are highly context dependent [5, 6, 30]. One reason for this is that the effects may be time-dependent: transitioning to regenerative farming can result in a short-term yield drop that recovers over time as soil fertility improves due to the adopted management practices themselves [6]. Ultimately crop yields may even move beyond the levels under conventional farming. In our base scenario we assume therefore yield drops of 6%, 4% and 2% in the first three years under regenerative farming practices respectively, recovering fully during year 4. From year 5 onward we assume yields are 2% greater than under conventional farming.

In terms of revenues from carbon credits, calibrating the market dynamics for voluntary markets can be difficult. Demand for carbon credits can depend significantly on the underlying projects that have generated the carbon credits. Markets are opaque, illiquid or both. Historic data on the trade in nature based carbon offsets is difficult to find. Data availability is better in case of compliance markets like the EU's Emissions Trading system, but price dynamics for these cap and trade systems are not representative for voluntary carbon markets. For our purposes we will therefore use the N-GEO futures contracts that are based on "nature-based offset projects" sourced from the Verra's registry. These are "projects that fall under the Agriculture, Forestry, or Other Land Use (AFOLU) categories". At the start of the 2023 calendar year the prices of these carbon credits hovered around \$5 for 1 metric ton of removed/reduced CO2e, we will use this value for $S(0)$. Due to a lack of price history, it is difficult to fit a geometric Brownian motion to the available data. We therefore set values for the market volatility and growth rate by assumption: $\sigma = 0.2$ and $\mu = 0.06$. In Section 3 and **Appendix B** (see **Figure A1**) we will perform a sensitivity analysis with respect to these parameters in order to assess their impact on modelling results.

The aforementioned USDA survey also publishes data on the average amount of acres farmer's plant of a particular crop for a given region. For the heartland region it indicates an average corn acreage of 302. We will adopt this as our default value for the parameter A. Farms typically have more acres that are planted with different crops: the average size of US farms that planted corn amounted to 725 acres in 2017. However, only acres that are planted with corn are taken into account for the analysis. Furthermore, the averages do not indicate how land is distributed among different farmers. According to USDA figures roughly 90% farmers could be considered small scale farmers in 2015, whereas the same group of farmers controlled less than 50% of acres. For large scale farmer the adopted value of 302 corn acres will therefore most likely be an underestimation. Section 3 provides a sensitivity analysis on how corn acreage is linked to incentives to adopt regenerative farming practices.

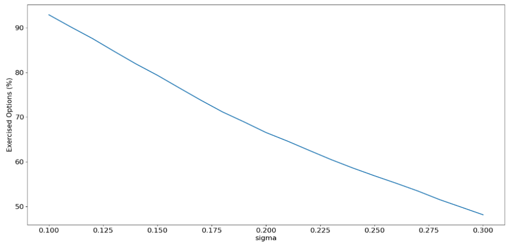
Note how we have assumed the investment costs I are an exogenous input variable, i.e. no link with the scale of the farming operation A has been modeled. The relationship between these two variables will affect to what extent the optimal trigger level will depend on the scale of the farming operation.

Finally we set the discount rate r by assumption to 0.10, we will test the effect of this variable on model outcomes by performing a sensitivity analysis, see **Figure A1** in **Appendix B**.

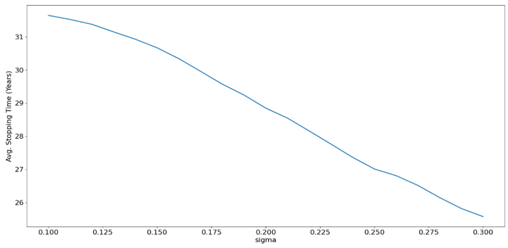
3. Results

To isolate the effect of variables of interest on the willingness of farmers to adopt regenerative farming practices, we can alter parameter values in a ceteris paribus manner. Given the large number of input parameters, the model allows for a great number of different scenarios. We focus here on three scenarios: the effect of carbon credit price volatility (**Figure 4**), the amount of corn acreage (**Figure 5**) and fertilizer reduction (**Figure 6**). The first scenario displays how the "wait and see" tendency of farmers is dependent on the degree of decision making uncertainty, the second investigates economies of scale, while the third scenario indicates how individual practice changes shape incentives for farmers.

Per scenario we present three output variables. As displayed in **Figure 2**, we derive the percentage of paths that adopt regenerative farming, as well as the average stopping time (in terms of years) for the paths that switch policies. Corresponding to **Figure 3** we present the option investment trigger and compare it to the trigger suggested by the net present value rule.



(**a**)



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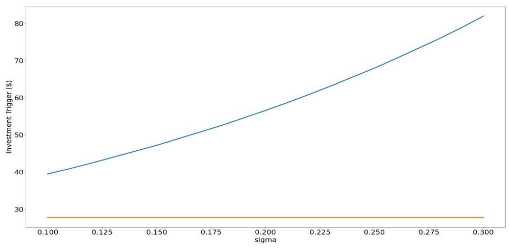
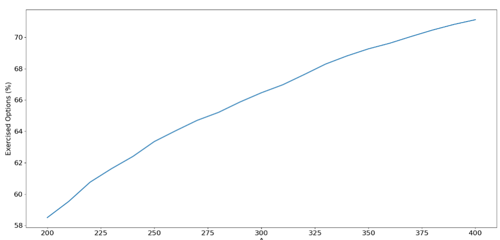


(**c**)

Figure 4. Simulation results as a function of carbon credit price volatility . The displayed output variables are the percentage of exercised options (**a**), the average stopping time (**b**) and the optimal investment trigger levels (**c**) according to the real option analysis (blue) and the net present value rule (orange).



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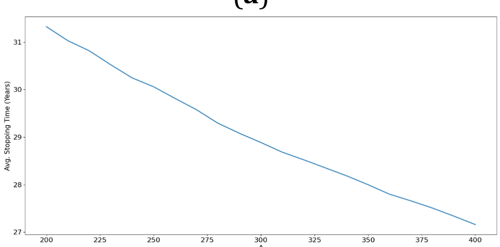
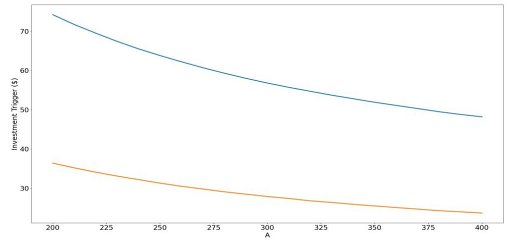


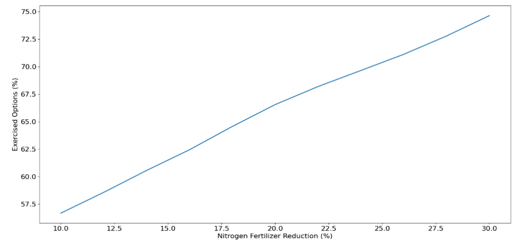
(**b**)

Figure 5. *Cont.*



(**c**)

Figure 5. Simulation results as a function of corn acreage. The displayed output variables are the percentage of exercised options (**a**), the average stopping time (**b**) and the optimal investment trigger levels (**c**) according to the real option analysis (blue) and the net present value rule (orange).



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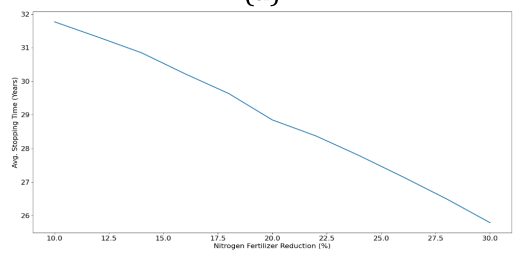

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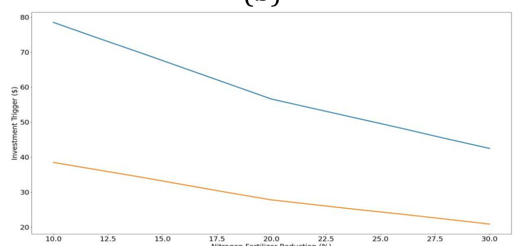

(**c**)

Figure 6. Simulation results as a function of nitrogen fertilizer reduction. The displayed output variables are the percentage of exercised options (**a**), the average stopping time (**b**) and the optimal investment trigger levels (**c**) according to the real option analysis (blue) and the net present value rule (orange).

4. Discussion

In the following three subsections we discuss the results corresponding to the three scenarios presented in the Section 3. A final subsection comments on the limitations of the analysis.

4.1. Carbon Credit Price Volatility

Investment options act as an insurance against market downturns; as long as the option to switch to regenerative farming has not been exercised, the negative impact from an unforeseen drop in the price of carbon credits on the value of the farm can be avoided. In general, insurances are more valuable in environments with a greater amount of uncertainty. Within the present context, this uncertainty is expressed by the carbon market volatility parameter σ. Correspondingly, a greater value of σ should drive the value of the investment option of switching to regenerative farming upwards.

Whenever the option value rises, the opportunity costs of switching to regenerative farming become larger: the moment the investment decision is taken, the insurance against market volatility provided by the option is lost. Intuitively this enhances the "wait and see" effect that farmers may exhibit. As a consequence, farmers will wait for the carbon credit price to reach a higher level before they are confident that switching practices is the right way forward. In other words, the investment trigger (i.e. the carbon credit price that triggers a practice switch) rises as σ increases, see the blue curve in **Figure 4c**. The estimated investment trigger ranges from \$39.5 to \$82.0 for a 10%–30% market volatility range. The economic significance of this effect can therefore be considerable, especially when comparing how far these estimates are removed from the price level of \$5 at the start of 2023 (i.e. our value for $S(0)$).

We can compare the investment trigger level resulting from option analysis with the trigger level derived from a net present value approach, see the orange curve in **Figure 4c**. Because the net present value methodology does not take into account the opportunity costs of exercising the investment option, investment is initiated already at \$27.8. Furthermore, because at any moment in time the carbon price volatility does not impact the expected returns derived from moving to regenerative farming, the net present value trigger does not react to σ. Given that voluntary carbon markets are considered to be volatile in nature, not acknowledging the impact of option effects on the transition of farmers to regenerative forms of agriculture can therefore lead to significant over-optimism.

Figure 4a shows that the number of paths that adopt regenerative farming decreases when σ rises. Because the investment trigger increases with greater carbon credit price volatility, fewer paths cross the relevant threshold. Among the paths that do switch practices, the average stopping time drops with greater volatility, see **Figure 4b**. Even though a higher investment threshold may cause farmers to switch later, greater price volatility also increases the probability that a sudden price spike crosses the investment trigger level. This latter effect dominates.

There are more sources of uncertainty that farmers may potentially face besides volatile carbon credit prices. In practice cash crop prices are volatile as well, in contrast with the assumption of a fixed cash crop price level that we have adopted here. There may be interaction affects between different sources of uncertainty. For instance, in case cash crop prices are volatile, one hypothesis could be that farmers face an incentive to diversify their income streams, which would make adopting regenerative farming relative more attractive. This remains a topic for future research.

4.2. Corn Acreage

The size of the farming operation is an important variable to consider: we can make more detailed predictions about the future adoption of regenerative farming for different types of farms if we know how the adoption rate of regenerative farming practices differs by the number of acres.

The blue curve in **Figure 5c** shows how the real option investment trigger level is a decreasing function with respect to the planted acreage of corn, i.e. large farming operations would switch more quickly to regenerative farming practices than smaller farms. The main driver behind this result are the assumptions regarding the investment costs I. We have determined these costs exogenously, in particular they do not scale with A. This creates economies of scale: because larger farms generate more revenue, the fixed investment costs become relatively less impactful. To the extent that in reality any new machinery, learning costs, etc. related to switching states are indeed independent of farm size, we can expect larger farms to be early adopters, whereas smaller farms will wait longer until carbon markets are more mature.

The assumed economies of scale that result in a negative relation between farm size and the investment trigger level is unrelated to any option effects: the same relationship holds true for the net present value method (orange curve). For any farm size however, the investment threshold under the option approach is roughly twice the net present value level. This once more shows the relevance of modeling "wait and see" behavior among farmers in the present context.

The 2022 USDA survey on commodity cost and returns indicates for corn an average of 302 planted acres per farm. At this size level, the option trigger level lies at \$56.6 per credit. However, as discussed in Section 2 the distribution of farms sizes in the US is skewed with about 50% of total acreage concentrated at the 10% largest farms. Regenerative farming programs may therefore prove most successful in terms of removing significant amounts of CO_2/reducing CO_2e emissions by initially targeting larger farmers with a relatively high value of production, as for these farmers it is optimal to switch practices at comparatively low carbon credit price levels. This is further supported by **Figure 5a,b**: more corn acreage increases the probability of switching to regenerative farming and adoption takes places earlier.

4.3. Fertilizer Reduction

Next to reducing tillage and introducing cover crops, we have assumed nitrogen fertilizer reduction as one of the practice changes that the farmer implements as part of a switch to regenerative farming. In our baseline simulations we have assumed a 20% reduction of nitrogen fertilizer applications specifically, see also **Appendix A** for more details. The current modeling set-up allows us to adjust the intensity of individual practice changes and see how this impacts the value proposition to the farmer. Here we will investigate to what extent the degree of fertilizer reduction shapes farmer's incentives to switch to regenerative practices.

Overall nitrogen fertilizer reduction has a threefold effect on the value of the farm. First, using less fertilizer saves on input costs. The USDA survey reports on fertilizer costs separately. We adjust these costs by 1% decrease for every 1% reduction in fertilizer usage.

Second, limiting nitrogen fertilizer application will impact the generation of carbon credit revenue. We have carried out a series of COMET Farm simulations where we iteratively adjust nitrogen fertilizer levels to assess the impact on $\delta(s)$. These simulations show that reducing nitrogen fertilizer application typically lowers $\delta(s)$. Although emissions of N_2O are reduced when less nitrogen fertilizer is applied, the amount of carbon sequestered drops as well. In terms of CO_2e the carbon sequestration effect dominates the prevented N_2O emissions.

Finally, reducing nitrogen fertilizer will affect crop yields $y(s,t)$ as well. To reflect this, we will adjust the time schedules imposed to simulate short-term yield drops and long-run soil fertility induced yield increases. In particular, we will assume that every 10% reduction in fertilizer usage during the intervention will lead to a crop yield drop of 3%, 2% and 1% for the first three years after switching states respectively, and an indefinite increase in crop yields by 1% from year 5. However, in order to prevent ever rising yields resulting from larger and larger reductions in fertilizer usage, we cap the increase in crop yields at 2% in total (i.e., there will be no further yield increases beyond a 20% reduction in fertilizer usage).

The mentioned effects work in different directions. The cost effect will incentivize farmers to change states more quickly, as it results in a cost reduction. The larger this cost reduction, the greater the willingness to transition. The carbon credit generation effect works in the opposite direction, since $\delta(s)$ drops when less fertilizer is applied. This leads to a lower revenue generation from carbon credits, making regenerative farming less attractive. The impact of the crop yield effect is more ambiguous: a greater yield drop disincentives switching states, but the eventual increase in soil fertility incentivizes it instead.

Figure 6c shows how both the option and net present value investment triggers become smaller when the fertilizer reduction gets larger, the effect seems to be roughly linear with a kink at a fertilizer reduction level of 20%. This is the point where the maximum long run crop yield increase of 2% is reached, so beyond this point further fertilizer reductions only create a larger short-term yield drop. From this we can derive that the cost effect dominates over the other two effects. As before, volatile carbon credit prices generate "wait and see" behavior, causing the option trigger level (blue) to significantly outrank the net present value trigger level (orange). We also observe once more how a lower trigger level corresponds to greater and faster adoption of regenerative farming (**Figure 6a**,**b**).

The performed calculations for the degree of nitrogen fertilizer applications can be repeated for other practice changes. In this way it is plausible to form a view about the economic effect of each individual practice change, or combinations thereof. This allows for the optimal configuration of regenerative farming practices, i.e. defining the collection of practices that incentivizes adoption by farmers to the greatest extent. Furthermore, the model could be used to advise farmers on the optimal moment to switch to regenerative farming. The validity of such exercises do hinge strongly on an accurate calibration of the model, for which detailed farmer data is imperative.

4.4. Limitations

During our analysis we have a made a number of simplifying assumptions that may impact model outcomes. For one, we have presumed farmers can make the decision of switching practices only once per crop year, at the start of the season. In reality there may be practices that can be introduced independently later down the crop year, leading to more decision-making flexibility. Introducing this into the model would require a careful analysis of what practices could be introduced when and how this would affect the carbon sequestration process. The complexity this would add, makes annual decision making a useful abstraction.

Similarly also the staging at which certain practices are introduced over the course of several years can be more flexible than we have assumed. In our modeling set-up the farmer has to make a strict choice between two sets of practices from one year to another, there is no middle ground. In reality it may be better to think of regenerative farming practices as a spectrum, for instance rather than going from heavy tillage to no tillage at all, the farmer could first experiment with reducing the tillage intensity. This would reduce implementation risk. Although the COMET farm model would allow for simulations with a set of transition practices, we have opted not to do so as our aim has not been to model such implementation risk. Instead, all uncertainty in our analysis is derived from the stochastic evolution of carbon credit prices.

As highlighted before, in reality farmers are facing many other forms of uncertainty that may influence their decision to switch to carbon credit prices. Fluctuating cash crop prices can interact with the yield effects regenerative farming generates. And volatility in the prices of fertilizer and seeds would introduce cost uncertainty. To simplify the analysis, we have limited our scope to a single source of uncertainty. Results should therefore also be interpreted in this context, option effects that have been generated due to carbon credit price fluctuations may also show up for other sources of uncertainty, causing interaction effects. This remains a topic for future research.

A further assumption we have made is that farmers cannot switch back to conventional farming. Alternatively, we could assume that upon exercise the regenerative farming investment option, farmers gain a new option to return to the previous state. Whether such an option to switch back would be likely to be exercised depends on the economic incentives farmers face after adopting regenerative farming, i.e., how farming costs and yields are affected. In scenarios where the costs of cover crop seeds are smaller than the cost savings on fertilizer, operational costs are reduced under the regenerative state. This would limit incentives to switch back. Furthermore, the adopted assumptions on how yields are impacted under regenerative farming assure that the possibility of returning back to conventional practices is mostly of relevance when considering the short run. The first few years after switching states a yield dip takes place. In the long-run farmers may actually benefit from increases in yield as soil fertility improves. This would have the effect of locking in farmers in the regenerative state as yields would drop back to conventional levels when corresponding practices are reintroduced. Overall, the ability to switch states would lower the regenerative farming investment trigger as it creates more flexibility, but the effect may be limited under current assumptions.

In our analysis we have focused on corn farmers for simplicity. Presuming sufficient calibration data is available, the model could equally be applied to other crops like e.g., soybeans and wheat. The COMET farm model has wide number of agricultural commodities that can be used to specify simulations, this includes the possibility to implement crop rotations. Similarly, we also included only three farming practices in the analysis. However, many more regenerative practices are possible, both in practice and when using the COMET farm tool.

Finally, both the real option and net present value methodologies have more general limitations as a predictive framework for farmer investment behavior and more alternative explanations have been proposed in the literature. Ihli et al. provide an overview of sociodemographic factors and farm(er) specific characteristics that are theorized to impact farmer decision making [20]. They designed an experimental set-up where farmers are asked to consider (dis)investments in irrigation technology. In their experiment they find that the risk attitude, age and education of the farmer, as well as farm and household size have a significant impact on farmer behavior. They also find some evidence of learning effects: when farmers have the opportunity to learn from their previous investment behavior they adept by delaying their moment of investment over time. Real option analysis as a theory to describe farmer investment behavior is therefore not complete and should be placed in a broader context of explanatory factors.

5. Conclusions

Farmers have the potential to remove greenhouse gases from the atmosphere via carbon sequestration, achieved by applying regenerative farming practices. However, wide scale adopting of these measures is complicated because the costs of implementation accrue to the farmer, whereas the benefits are distributed to the broader society. Carbon markets form a possible mechanism to help resolve this externality problem by providing farmers with an additional income stream for sequestered carbon in the form of carbon credit sales.

The economic viability of carbon markets depends on the significance of the incentives the carbon credit mechanism can provide to farmers as to motivate them to switch towards regenerative farming practices. Our research contributes to the literature of carbon markets by assessing in significant detail what factors shape these incentives. In particular we have described how real option analysis can be applied to establish the optimal investment timing for farmers to switch from conventional farming practices to regenerative farming. The developed modeling approach puts special emphasis on the “wait and see” attitude that underlies this investment decision, this behavioral effect is not captured in commonly applied net present value analyses. We have shown that omitting the tendency of farmers to remain flexible in their decision making from analysis can lead to overoptimistic predictions regarding the willingness to adopt regenerative farming. In general, the greater the volatility of carbon credit prices, the more relevant this “wait and see” behavior becomes. At an annualized volatility level of 20% the effect is strong enough to roughly double the required carbon credit price to incentivize farmers to adopt regenerative farming practices.

Prior research has indicated that depending on where carbon credit prices range between \$20-\$100, there exists a global carbon sequestration potential ranging from 400 to 1200 million tons per year [10]. Comparatively our simulations show that for a representative farmer located in the US state of Iowa a price level of roughly \$60 per carbon credit provides the tipping point where the typical corn farmer faces sufficient incentives to consider adopting regenerative farming practices. This estimated price level can vary considerably depending on the specific characteristics of the farming operation, such as adopted practices, production costs and, specifically, acreage. Economies of scale ensure that large farming operations have a lower investment boundary to switch to regenerative farming practices than smaller farms do. This effect can be considerable: we estimate that a farmer with 200 acres of corn requires a carbon credit price of roughly \$78, whereas a farmer with double the amount of corn acreage would have a threshold of about $48 instead.

Our advice to policy makers is to consider that to reach sufficiently high adoption rates under a carbon credit model, incentives should not only cover potential increases in farming costs due to regenerative farming practices, but also need to convince farmers to give up decision making flexibility. Because voluntary carbon markets have not fully matured yet, carbon credit prices can currently fluctuate wildly, which makes farmers more hesitant to switch systems. Securing farmers with more predictable income streams, for instance by providing insurance against carbon credit price volatility or other risks inherent to adopting regenerative farming practices, will aid in improving incentives by lowering investment thresholds to net present value levels. Furthermore, the targeting of farmers for joining regenerative farming programs should be aimed at groups with relatively low investment threshold levels, like farmers with sufficient acreage of corn.

Finally, next to the descriptive purpose, i.e. highlighting how farmer behavior is affected when the underlying investment environment changes, the developed modeling approach can also be used in a normative manner: presuming sufficient calibration data is available the model can suggest optimal investment strategies for individual farmers. As such the model can be considered an economic module on top of the biochemical COMET Farm model. By running particular sets of farming practices the yield of carbon credits can be determined, which allows the real option model to estimate the optimal trigger level under which the farmer should adopt regenerative farming practices. As an example, we have shown how different levels of nitrogen fertilizer application should affect farmer's decision making.

Author Contributions

Conceptualization, B.J.S., B.E.B.; methodology, B.J.S., B.E.B., T.S.; formal analysis, B.J.S., T.S.; writing—original draft preparation, B.J.S., B.E.B., T.S.; writing—review and editing, B.J.S., B.E.B., T.S.; supervision, B.E.B.; All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

All input data to the model that can be disclosed has been referenced in the main text or in the appendix A, for further inquiries contact the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

Appendix A. Calibration Details

In this appendix we specify the base scenario for our simulations in more detail, and we provide a breakdown of the farming costs taken into consideration.

Before the intervention, we assume the farmer uses intensive tillage, does not plant cover crops and has a high nitrogen fertilizer usage. After switching, no tillage will be applied at all, and the usage of nitrogen fertilizer is reduced. Furthermore, vetch will be planted every year as a cover crop. We select vetch because COMET simulations indicate it generates more carbon sequestration than other cover crops such as cereal rye. **Table A1** provides a summary of all the selected parameter values for the base scenario. The listed values have been selected mostly because they are defaults provided by the COMET Farm tool.

Based on the above specification, the COMET farm tool indicates 1.075 metric tons of CO2e per acre can be removed/reduced on a yearly basis. We adopt this value for $\delta(1, t)$.

In terms of farming costs we have adopted the

Table A1. Summary of the adopted farming practice values under the conventional and regenerative states.

Parameter	Farming Practice	
	Conventional	**Regenerative**
Cash Crop Planting Date	6th of May	
Cash Crop Harvest Date	22nd of November	
Cover Crop Type	N.A.	Vetch
Cover Crop Planting Date	N.A.	23rd of November
Cover Crop Harvest Date	N.A.	29th of April
Tillage Method	Intensive Tillage	No Tillage
Tillage Date	5th of May	N.A.
N Fertilizer Type	Urea Ammonium Nitrate (30-00-00)	
N Fertilizer Amount	130.3 lbs/acre	104.2 lbs/acre
N Fertilizer Application Method	Surface Band/Sidedress	
N Fertilizer Application Date	6th of May	

cost entries in $c(t)$ and associated values in the **Table A2**. These are derived from USDA recent cost and returns dataset for corn, the heartland region, year 2022. During our simulations we keep these values fixed over time. When applying fertilizer reduction by a certain percentage under the intervention, we will reduce fertilizer costs on a one-by-one basis. Upon the introduction of cover crops we increase seed costs by 50%.

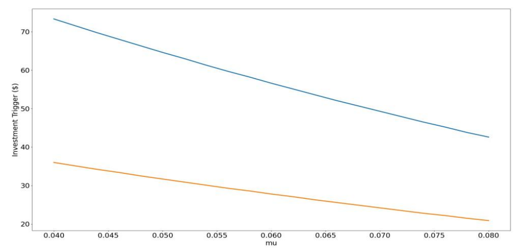
Table A2. Summary of the adopted values for cost parameters.

Cost Parameter	Value ($/Acre)
Seed	100.96
Fertilizer	228.65
Chemicals	44.30
Custom Services	27.15
Fuel, lube and electricity	40.19
Repairs	39.89
Interest on operating capital	5.87
Hired labor costs	4.30
Opportunity costs of unpaid labor	32.30
Capital recovery of machinery and equipment	173.36
Opportunity costs of land	210.98
Taxes and insurance costs	13.95
General farm overhead costs	22.01

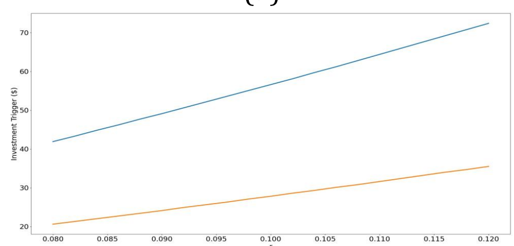
Appendix B. Sensitivity Analysis

To assess how the model results respond to the values adopted for the most important parameters, we perform a sensitivity analysis. **Figure A1** indicates how the trigger level is dependent on the expected carbon credit price growth rate μ, the discount rate r, the investment costs I and the saturation time $\bar{T}$ respectively.

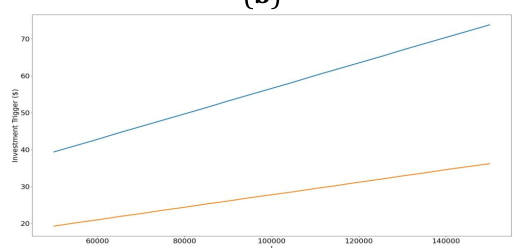
Increasing the expected growth rate for carbon credit prices μ directly raises the reward from switching practices as the expected stream carbon credit revenue will be larger, improving the net present value of the investment. This makes the investment proposition more attractive, which puts downward pressure on the trigger level: as visible in **Figure 5a** the trigger level drops when μ grows larger. This holds both for the option model (blue) as well as the net present value model (orange).



(**a**)

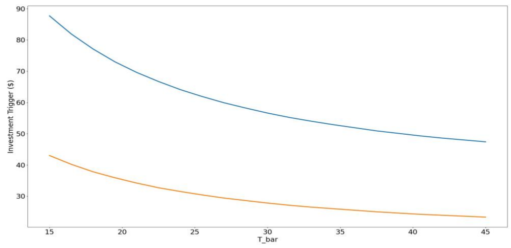


(**b**)



(**c**)

Figure 7. *Cont.*



(**c**)

Figure 7. The real option trigger level (blue) and the net present value trigger level (orange) as a function of the expected carbon credit price growth rate (**a**), the discount rate (**b**), the investment costs (**c**) and the saturation time (**d**).

The discount rate r is a difficult parameter to calibrate, as it reflects the value the farmer attaches to time, which may differ from individual to individual. A larger discount rate makes the far future less important. Under our assumptions switching to regenerative farming requires upfront investment costs and generates a short-term yield drop, whilst carbon credit revenues are only received over the course of multiple decades. Therefore, farmers with a high value for r, i.e. a strong focus on the immediate future, will be relatively difficult to convince to adopt regenerative farming. **Figure 5b** shows that this effect can be strong: increasing the discount rate by 50% can roughly double the required trigger level.

Farmer behavior also reacts sensitively to the investment costs parameter I. Raising the investments costs from $50.000 to $150.000 increases the required trigger level from $39.4 to $73.8, see **Figure 5c**. Any measures reducing the costs of switching to regenerative farming practices are therefore crucial in improving the adoption rates of regenerative farming under a carbon credit system.

The level of $\bar{T}$ determines how long it takes before no more carbon can be sequestered and/or no further carbon credits can be issued. The longer this period continues, the greater the sum of the discounted revenue streams from carbon credits will be for farmers. A higher value of $\bar{T}$ therefore makes regenerative farming more attractive and reduces the trigger level (see **Figure 5d**). Presuming contractual factors are not limiting, this result also indicates that the carbon credit system may reward farmers differently based on their past behavior. Farmers who previously applied intensive farming practices that deteriorated soil health may have a relatively large $\bar{T}$ because at the onset carbon soil stocks have been depleted significantly compared to the saturation level. In contrast, farmers who paid more attention to soil carbon stocks to begin with may have a relatively small value for $\bar{T}$, which reduces the incentives to further adopt regenerative farming practices.

References

[1] Crippa, M., Guizzardi, D., Pagani, D., et al, 2023. Ghg Emissions of All World Countries. DOI: https://doi.org/10.2760/953332, JRC134504

[2] Toensmeier, E.,L 2016. The Carbon Farming Solution: a Global Toolkit of Perennial Crops and Regenerative Agriculture Practices for Climate Change Mitigation and Food Security. Chelsea Green Publishing: White River Junction, VT, USA. p. 12.

[3] Khangura, R., Ferris, D., Wagg, C., et al., 2023. Regenerative Agriculture — A Literature Review on the Practices and Mechanisms Used to Improve Soil Health. Sustainability. 15, 2338. DOI: https://doi.org/10.3390/su15032338

[4] Schreefel, l., Schulte, R., de Boer., I., et al., 2020. Regenerative Agriculture - the Soil is the Base. Global Food Security. 26. DOI: https://doi.org/10.1016/j.gfs.2020.100404

[5] Ponti, T., Rijk, B., Ittersum, M.V, 2012. The Crop Yield Gap between Organic and Conventional Agriculture. Agricultural Systems. 108, 1–9.

[6] Rosa-Schleich, J., Loos, J., Mußhoff, O., et al., 2019. Ecological-economic Trade-offs of Diversified Farming Systems - a Review. Ecological Economics. 160, 251–263.

[7] Alexander, P., Paustian, K., Moran, D., 2015. The Economics of Soil C Sequestration and Agricultural Emissions Abatement. SOIL. 1, 331–339.

[8] Thompson, N., Hughes, M., Nuworsu, E., et al., 2022. Opportunities and Challenges Associated with "Carbon Farming" for US Row-crop Producers. Choices. 27(3), 1–10.

[9] Plastina, A., Haeun, J., Wongpiyabovorn, O., 2024. The Business Case for Carbon Farming in the USA, Carbon Balance and Management. Choices. 7(19). DOI: https://doi.org/10.1186/s13021-024-00253-5

[10] Smith, P., Martino, D., Cai, Z., et al., 2008. Greenhouse Gas Mitigation in Agriculture. Philosophical Transactions of the Royal Society B. 363, 789–813.

[11] Kreibich, N., Hermwille, L., 2021. Caught in Between: Credibility and Feasibility of the Voluntary Carbon Market Post-2020. Climate Policy. 21(7), 939–957.

[12] Miltenberger, O., Jospe, C., Pittman, J, 2021.

The Good is Never Perfect: Why the Current Flaws of Voluntary Carbon Markets are Services, not Barriers to Successful Climate Change Action. Frontiers in Climate. 3, 686516. DOI: https://doi.org/10.3389/fclim.2021.686516

[13] Wongpiyabovorn, O., Plastina, A., Crespi, J., 2022. Challenges to Voluntary Ag Carbon Markets. Applied Economic Perspectives and Policy. 45(2), 1154–1167.

[14] Dixit, A., Pindyck, R., 1994. Investment under Uncertainty. Princeton University Press: Princeton, NJ, USA.

[15] Purvis, A., Boggess, W., Moss, C., et al., 1995. Technology Adoption Decisions under Irreversibility and Uncertainty: an Ex ante Approach. American Journal of Agricultural Economics. 77, 541–551.

[16] Winter-Nelson, A., Amegbeto, K., 1998. Option Values to Conservation and Agricultural Price Policy: Application to Terrace Construction in Kenya. American Journal of Agricultural Economics. 80, 409–416.

[17] Odening, M., Musshoff, O., Balmann, A., 2005. Investment Decisions in Hog Finishing: An Application of the Real Options Approach. Agricultural Economics. 32, 47–60.

[18] Seo, S., Segarra., E., Leatham, D. Irrigation Technology Adoption and Its Implication for Water Conservation in the Texas High Plains: A Real Options Approach. Agricultural Economics. 38, 47–55.

[19] Sanderson, T., Hertzler, G., Capon, T, et al., 2015. A Real Options Analysis of Australian Wheat Production under Climate Change. Australian Journal of Agricultural and Resource Economics. 60(1), 79–96.

[20] Ihli, H., Maart-Noelck, S., Musshof, O., 2013. Does Timing Matter? A Real Options Experiment to Farmers' Investment and Disinvestment Behaviours. Australian Journal of Agricultural and Resource Economics. 58, 430–452.

[21] Regan, C., Bryan, B., Connor., J., et al., 2015. Real Options Analysis for Land Use Management: Methods, Application, and Implications for Policy. Journal of Environmental Management. 161, 144–152.

[22] Hertzler, G., 2007. Adapting to Climate Change and Managing Climate Risks by Using Real Options. Australian Journal of Agricultural Research. 58, 985–992.

[23] Longstaff, F., Schwartz., E., 2001. Valuing American Options by Simulation: A Simple Least-squares Approach. The Review of Financial Studies. 14(1), 113–147.

[24] Woo, J., Liu, C., Choi, J., 2024. Leave-one-out least Square Monte Carlo Algorithm for Pricing Bermudan Options. The Journal of Futures Markets. 44(8), 1404–1428.

[25] Forsyth, P.A., Vetzal, K.R., 2002. Quadratic Convergence for Valuing American Options Using a Penalty Method. SIAM Journal on Scientific Computing. 23(6), 2095–2122.

[26] Lal, R., 1997. Residue Management, Conservation Tillage and Soil Restoration for Mitigating Greenhouse Effect by CO2-enrichment. Soil Tillage Research. 43, 81–107.

[27] Poeplau, C., Don, A., 2015. Carbon Sequestration in Agricultural Soils via Cultivation of Cover Crops – A Meta-analysis. Agriculture, Ecosystems and Environment. 200, 33–41.

[28] Hijbeek, R., LOON, M.V., Ittersum, M.V., 2019. Fertiliser Use and Soil Carbon Sequestration: Opportunities and Trade-offs. Available from: https://edepot.wur.nl/495104

[29] Schnitkey, G., Swanson, K., Paulson, N., 2022. Inflation and Commodity Prices. Farmdoc Daily. 60(93).

[30] Oldfield, E., Bradford, M., Wood, S., 2019. Global Meta-analysis of the Relationship between Soil Organic Matter and Crop Yields. SOIL. 5, 15–32.