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From Farm to Planet: The InSEEDS World-Earth Model for Simulating Transitions to Regenerative Agriculture

Luana Schwarz[1,2,3,4*], Jannes Breier[1,2,5], Hannah Prawitz[1,2,6], Max Bechthold[2,6], Werner von Bloh[2], Sara M. Constantino[7], Dieter Gerten[2,5], Jobst Heitzig[2], Ronja Hotz[8], Leander John[2,9], Christoph Müller[2], Johan Rockström[2,3,10], and Jonathan F. Donges[1,2,10]

[1]Integrative Earth System Science, Max Planck Institute of Geoanthropology, Jena, Germany
[2]Potsdam Institute for Climate Impact Research, Member of the Leibniz Association, Potsdam, Germany
[3]Institute of Environmental Science and Geography, Potsdam University, Potsdam, Germany
[4]Institute of Environmental Systems Research, Osnabrück University, Osnabrück, Germany
[5]Institute of Geography, Humboldt University of Berlin, Berlin, Germany
[6]Institute of Physics and Astronomy, Potsdam University, Potsdam, Germany
[7]Doerr School of Sustainability, Environmental Social Sciences, Stanford University, Stanford, United States
[8]Institute of Meteorology and Climate Research - Atmospheric Environmental Research, Karlsruhe Institute of Technology, Karlsruhe, Germany
[9]Department of Physics and Astronomy, Heidelberg University, Heidelberg, Germany
[10]Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden

Correspondence: Luana Schwarz (schwarz@gea.mpg.de); Jonathan F. Donges (donges@pik-potsdam.de)

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Abstract.

Industrialised agriculture and its externalisation of environmental costs have contributed to accelerating ecological degradation and the transgression of planetary boundaries. Vice versa, agriculture is increasingly affected by ecological pressures such as climate change. While sustainable approaches like Regenerative Agriculture offer promising alternatives, most studies focus on the biophysical impacts of individual practices and overlook the complex dynamics underlying their large-scale adoption. In particular, the roles of social-ecological feedbacks, tipping dynamics, and transformative change remain underexplored. To address this gap, we introduce the InSEEDS integrated World-Earth model—a novel co-evolutionary approach to simulating agricultural transitions that couples a process-based vegetation model (LPJmL) with an agent-based model of farmer decision-making. InSEEDS integrates socio-cultural, social-ecological, and biophysical dynamics and can be applied from local to global scales. Distinguishing between a traditionalist and pioneer farmer types, we analyse the adoption dynamics of conservation tillage as a key practice of Regenerative Agriculture. We find that social networks, ecological heterogeneity, and decision-making inertia play a critical role in determining transition dynamics. Adoption of conservation tillage yields overall positive effects on soil carbon and crop yield, though outcomes are strongly context-dependent. InSEEDS provides a foundational tool that opens up avenues for understanding complex human-environment interactions in land-use transformations and advancing the next generation of World-Earth models.

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1 Introduction

Co-evolutionary dynamics between humans and the Earth system are the central characteristic of the Anthropocene, a new epoch in the evolution of the Earth system (Schellnhuber, 1999; Crutzen, 2002; Steffen et al., 2011). Agricultural systems are a prominent example of the co-evolutionary interactions in World-Earth Systems (Meyfroidt et al., 2022). By transforming natural into cultural landscapes, agricultural production has reshaped the biosphere for centuries. The green revolution is a specifically stark example this process: in the 1950s and 1960s, it intensified land use and agriculture, enabling global population growth and prosperity. However, this development has irrevocably changed the biosphere through the use of artificial fertilizers, intensive soil cultivation and the increase in water use for irrigation (Foley et al., 2005). As a result, the intensification of agricultural practices contributes significantly to environmental degradation (Pretty et al., 2018; Benton and Bailey, 2019). The result is the transgression of multiple planetary boundaries (PBs) – critical processes that sustain Earth System stability and resilience – such as biosphere integrity, land-system change, freshwater use or biogeochemical flows (Campbell et al., 2017; Richardson et al., 2023). Soil degradation is among the most significant problems, as it entails a loss of soil nutrients and soil organic matter (SOM), followed by decrease in the soil's water retention and infiltration capabilities. This can lead to a loss of soil water holding capacity, which is the ability of the soil to store and release water as needed, and eventual decreases in crop yields (Smith et al., 2021; Qiao et al., 2022). With increasing climate change and global warming, pressure from rising water consumption in the form of evapotranspiration and extreme weather events such as droughts and heat waves are also increasingly affecting agroecosystems, further intensifying the pressure on food production and security globally (Gordon et al., 2017). Given the critical reliance of societies on food and other ecosystem services provided by agricultural systems, a systemic transformation is imperative to ensure agricultural productivity while maintaining or re-establishing the ecological resilience of these systems (Benton and Bailey, 2019).

Regenerative Agriculture (RA) practices have been proposed as one approach to tackle some of the challenges posed by dominant approaches to conventional, industrialized agriculture. RA can involve a broad range of practices that vary depending on the regional biophysical and socio-cultural context. Most RA scholars and practitioners agree on soil health as the common core of RA practices (Schreefel et al., 2020). While the inclusion of livestock is often practised in RA, the paradigm is also applicable to crop-based systems (Kassam and Kassam, 2024). Conservation tillage (CT), a form of sustainable agriculture in which soil disturbance is minimised and permanent soil cover is maintained using plant residues, is one of these cropping system practices. Soil health has repercussions on multiple scales and is often regarded as a key leverage point for planetary health (Montgomery et al., 2024). However, RA has also been construed more broadly to refer to the restoration of agrobiodiversity and (re-)establishment of functional water cycles (Lal, 2020). Some scholars and practitioners explicitly include human, social, and societal dimensions in their definition of RA. Müller (2020) embeds RA within a broader paradigm he calls "regenerative development", which comprises societal dimensions like politics and economy, while Gosnell (2022) considers also the individual-level changes arising through RA practices. While some dimensions, most prominently ecological, of RA practices are well-researched (LaCanne and Lundgren, 2018; Lal, 2020; Kassam et al., 2022), the question of how transitions towards such systems can unfold is largely under-researched, and mostly limited to single case studies and

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geographical regions (Castilla-Rho and Kenny, 2022; Frankel-Goldwater et al., 2024). There are several outstanding research questions, aimed at understanding how such transitions might unfold, including: What could adoption and therefore spreading dynamics of RA look like given different social structures or learning processes? Can social tipping points be reached in those transition processes, such that positive feedbacks lead to widespread and self-reinforcing adoption? How can resilient agricultural land systems be achieved globally—and how might the process of adoption differ across locations? The aforementioned research questions cannot be addressed by existing modelling approaches due to divergent model purposes and lenses. Social-ecological, for example agent-based modelling approaches, capturing human behaviour and social dynamics in nuanced ways, are often limited in their range of applicability and, in many cases, applied to single case studies. Albeit larger-, up-to-global scale modelling approaches, like integrated assessment models that aim to include human dynamics in their analyses, exist, their understanding of “the human" is limited. Their macroeconomic optimization approaches rest on the rational actor paradigm and omit scientific findings about alternative motivations and drivers in human decision-making (Browning et al., 1999; Hodgson, 2012; Otto et al., 2020). To address the aforementioned questions and explore potential pathways for the widespread adoption of RA practices like CT, novel methodological approaches are required: co-evolutionary, large-scale social-ecological, coupled Human-Earth system, or World-Earth models (WEMs), with a closed social-ecological feedback loop that capture social and ecological processes in a multifaceted way, and account for the interaction of these two domains (Steffen et al., 2020; Farahbakhsh et al., 2022; Rockström, 2024). This approach can be regarded as complementary to existing approaches that have different analytical foci and theoretical lenses. Co-evolutionary models of human-land system interactions and change should consider integrated social-ecological dynamics of humans in the Earth System (Donges et al., 2017; Schill et al., 2019; Beckage et al., 2020; Farahbakhsh et al., 2022; Beckage et al., 2022; Moore et al., 2022), including novel concepts like the technosphere, higher levels of social organisation, or psychological-behavioural factors, like values, attitudes, and norms that do not appear in models focused on cost optimization and efficiency (Rounsevell et al., 2014). One central challenge of these efforts is moving beyond simple proof-of-concept models towards more complex, integrated models, as suggested by Beckage et al. (2020), which also consider biophysical preconditions and decision-making in a process-based manner.

Donges et al. (2020) proposed the copan:CORE modelling framework to help address this gap and build WEMs. These models are characterised by (1) the representation of social-ecological co-evolution at up-to-planetary scales, and (2) modelling social dynamics using a multitude of theoretical and methodological approaches. A model built in the copan:CORE modelling framework consists of entities that interact with each other via processes (Donges et al., 2020). These are categorized by three overlapping process taxa, representing biophysical (ENV, e.g. crop growth or SOM formation), socio-metabolic (MET, e.g. crop harvest or soil analysis) and socio-cultural (CUL, e.g. governance, social learning, social norms, or individual cognitive-behavioural processes like attitude formation) processes (Donges et al., 2021). Breier et al. (2024) advanced the framework by integrating the Dynamic Global Vegetation Model (DGVM) LPJmL as the main constituent of the ENV taxon to include detailed representations of agricultural systems (Jägermeyr et al., 2015; von Bloh et al., 2018; Lutz et al., 2019; Porwollik et al., 2022). This novel modelling framework for WEMs with a land system focus is called copan:LPJmL.

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Building on this work, here, we present the InSEEDS (**In**tegrated **S**ocial-**E**cological r**E**silient lan**D** **S**ystems) model, the first WEM model built with copan:LPJmL that integrates agent-based model components for socio-cultural and social-ecological dynamics. This model couples social and social-ecological dynamics in the MET and CUL taxa with biophysical dynamics represented by LPJmL. This way, InSEEDS is able to model the human-land system more holistically than prior efforts, providing insight into the conditions and drivers that enable a transition to more sustainable and resilient land and food systems. Our integrated modelling approach allows to capture co-evolutionary dynamics of farmer decision-making and agricultural processes on up to a global scale, and provides a tool to dynamically explore “what-if" future scenarios of up-to global land system change. Investigating the adoption of regenerative land management practices is particularly worthwhile due to its potential to increase Earth system resilience. Given the central role of land system management in the global change dynamics of the Anthropocene (Steffen et al., 2011; Campbell et al., 2017), the InSEEDS model allows for the embedding of land(scape) regeneration within planetary and Earth system stewardship (Chapin et al., 2011; Steffen et al., 2018; Rockström et al., 2024).

In this model, we introduce farming agents whose management decisions directly impact their agricultural systems, themselves, and their neighbours. Farmers choose between two different tillage practices and analyse their performance depending on their own attitudes, norms, and behavioural control, as well as the ecological performance of the different practices in terms of soil organic carbon (SOC) and crop yield (CY). InSEEDS simulations rest on LPJmL as a spatially-explicit, process-based, established vegetation model component and integrate this with a behavioural, agent-based model component, whose coupled setup allows for nuanced, up-to-planetary scale social-ecological analyses.

2 InSEEDS model description

The InSEEDS model captures interactions between social, ecological, and socio-cultural processes, structured across three interconnected process taxa: environmental (ENV), socio-metabolic (MET), and socio-cultural (CUL). This section introduces the core architecture of the InSEEDS model and outlines its key components: the biophysical simulation of land management practices (Chapter 2.1), the behavioural and networked dynamics of farming agents (Chapter 2.2), and the feedback mechanisms that close the loop between ecological outcomes and social adaptation. The model's design aims to enable the analysis of large-scale transitions in land use by simulating how different types of farmers adopt regenerative agricultural management practices under varying social and ecological conditions.

A complete model description following the ODD (Grimm et al., 2006, 2010) and ODD+D (Müller et al., 2013) protocols can be found in the supplementary material.

InSEEDS represents two different agricultural management practices that farmers can adopt, Conventional Farming (CF) and Conservation Tillage (CT); the latter is a central cornerstone of many RA operations worldwide. The agent-based component of the InSEEDS model – called regenerative tillage – describes how farmers make decisions about the management of their land (LPJmL input) based on ENV state variables (LPJmL output) (Chapter 2.2). Farmers observe CY and SOC (MET) as well as local social norms (CUL) and then make a decision about whether to engage in CF or CT. Each management strategy has a different agro-ecological impact. The chosen management practice is applied (MET), and the underlying biophysical

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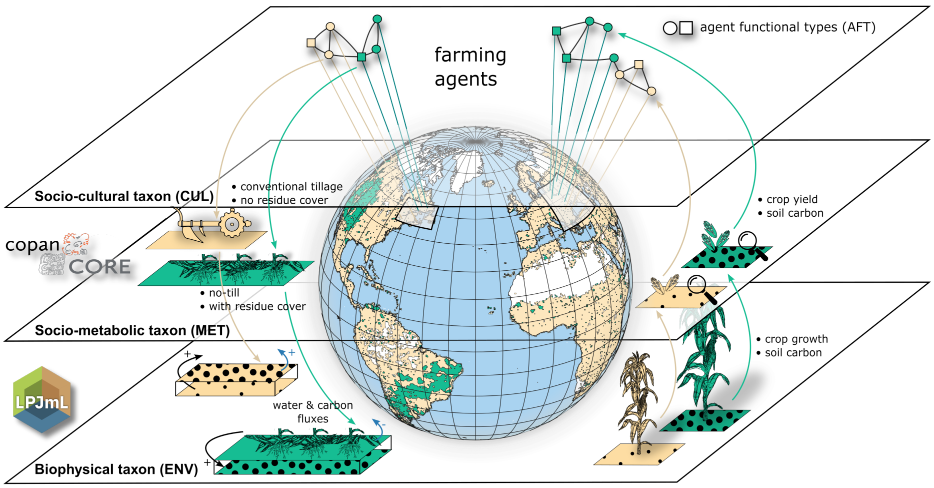

Figure 1. Schematic depiction of the processes prevalent in the socio-cultural (CUL), socio-metabolic (MET) and environmental (ENV) taxa in the InSEEDS model, following (Donges et al., 2021).

processes and consequences are simulated (ENV). The effects are then observed by the farmer in the form of CY and SOC (MET), closing the feedback cycle.

2.1 Environmental taxon: conservation tillage as a RA practice

The ENV taxon of InSEEDS simulates the ecological effects of different tillage systems. The combination of different soil-conserving tillage systems like no till, in-row subsoiling or strip till, with residues left on the field that cover more than 30% of soil surface can be summarised under the term CT (SARE, 2020). Tillage systems were introduced to LPJmL by Lutz et al. (2019). CF describes the use of conventional tillage without leaving residues on the field. In LPJmL, tillage systems are defined by these two dimensions: (1) whether to till (conventionally) or not to till (no till), (2) how much crop residue to leave on the field after harvesting (residue coverage). In LPJmL standalone simulations, tillage and residue coverage are commonly prescribed by static input data. In “regenerative tillage", both inputs are coupled and represented by a MET-ENV process, described in detail in Chapter 2.2. For simplicity, multiple options were reduced to two practices P for InSEEDS:

1. **Conventional farming** (CF) with tillage and a variable crop residue coverage prescribed by input data ($P = 1$)

2. **Conservation tillage** (CT) with no till and a maximum crop residue coverage (all residues remain on the field, $P = 0$), following (SARE, 2020)

LPJmL simulates the agro-ecological dynamics of both CF and CT based cropping systems. The long-term effects of this CT management system in LPJmL have been studied in Herzfeld et al. (2021). This study showed that, globally, the amount of crop residue has the largest impact on SOC, while no till in combination with crop residue increases SOC even more.

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Conservation Agriculture approaches, like CT, have been proposed as a fundamental cornerstone of RA systems (Kassam, 2023; Kassam and Kassam, 2024). The InSEEDS model, prospectively, is designed to investigate transitions to RA systems that comprise a diverse set of land-use management practices that go beyond CT. We chose CT as our first representative RA practice based on the observation that, as a single practice, it can be regarded as one of the options with the widest potential for adoption and positive outcome on ecological indicators (Wang et al., 2006; Liang et al., 2025). In the following, we use the terms CT and RA interchangeably, and elaborate on their connection in Discussion Section (5).

CY and SOC are two indicators for farming performance as a function of the chosen management practice P. While CY can be regarded as a momentary productivity snapshot that can be volatile and change in response to changing environmental conditions like extreme events (such as droughts, floods) or erosion, SOC can serve as a more long-term resilience metric for farmers (Bossio et al., 2020).

Effects of CT practices on CY show mixed results regionally, but exhibit a general global trend towards increases in CY under CT compared to CF (Lutz et al., 2019) practices due to reduced soil evaporation, increased root zone soil moisture, and increased SOC, which entails higher water availability, especially in dry regions (Pittelkow et al., 2015; Lutz et al., 2019).

CT is the most effective management practice in the LPJmL model in terms of its effects on global SOC levels. Nevertheless, Herzfeld et al. (2021) also showed that CT does not necessarily lead to an increase in SOC, a pattern that has been shown by Karstens et al. (2020). This can be partly attributed to legacy fluxes from past changes in land use. For example, if a forest patch was recently converted to cropland, SOC levels might continue to decrease under any agricultural management option in the short term, as those options would not compensate for the high SOC levels resulting from natural vegetation. However, SOC might decrease less under CT in contrast to CF, indicating that CT still has an overall positive effect on SOC levels in already converted agricultural lands. Slow responses of SOC levels to short-term agricultural management changes might play another role in the limited effects of CT practices in modelling studies.

2.2 Socio-cultural and metabolic taxa: social-ecological dynamics of management changes

Understanding and modelling the social dynamics of the adoption and spread of agricultural practices in farmer networks is a multi-disciplinary endeavour. Our conceptualisation and implementation of the ABM component of the InSEEDS model is informed by literature from the social sciences. Here, we briefly review the theoretical and empirical foundations of the ABM, as well as their formal implementation in the model. We begin by elaborating on agent decision-making, which also includes the role of the agents' interactions with their social and ecological environment. We then introduce the concept of agent functional types (AFTs) and specify the AFTs prevalent in the model.

The farmer's decision-making depends on two feedback loops, characterised by different interactions within the agent-based model (see Figure 2): The social feedback loop is characterised by agents observing the social norms present among their neighbours. The social-ecological feedback loop represents how the farmers' interaction with their biophysical environment, through information about the SOC content and CY, shapes their attitudes. Both social norms and attitudes contribute to the decision about which land management practice the farmers adopt.

Agent decision-making and interactions

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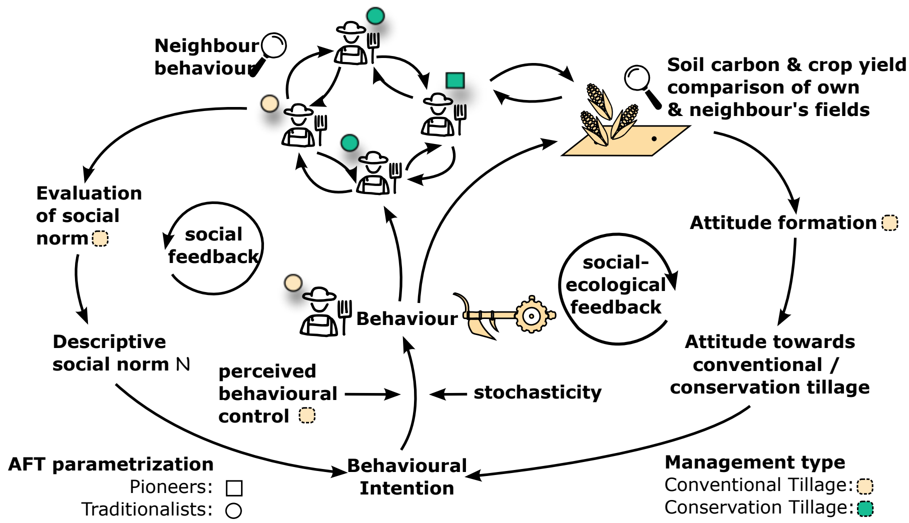

Figure 2. Representation of the InSEEDS ABM component's feedback loops and the operationalisation of the Theory of Planned Behaviour, own adaptation from Ajzen (1985). The shapes adjacent to the farmer agents depict the different AFTs, while to colours of the shapes depict the currently practised management style.

Decision-making of the farmer agents in our model is rooted in the Theory of Planned Behaviour (TPB) (Ajzen, 1985). The TPB is a well-established theory from cognitive psychology, which has been applied to a wide range of contexts, including environmental decision-making (Bamberg, 2013; Yuriev et al., 2020; Swart et al., 2023). It is formalised as follows:

The TPB posits that human action is driven by behavioural expectations BE—a combination of perceived behavioural control PBC and behavioural intention BI:

$$BE_i = BI_i \cdot PBC_i. \tag{1}$$

PBC describes the perceived ease or difficulty of performing a given behaviour. Its determinants are described in detail below.

According to the TPB, behavioural intentions BI are driven by two factors: (1) attitudes A, and (2) subjective norms N. Attitudes and subjective norms have different weights in the decision, ω_A and ω_{nbr}, depending on the AFT, described in detail below. This yields:

$$BI_i = (\omega_A \cdot A_i + \omega_{nbr} \cdot N_i). \tag{2}$$

Attitudes describe the individual evaluation of a given behaviour. Subjective norms describe the perceived social pressure to perform a given behaviour inferred from the prevalent behaviours among a farmer's neighbours (the descriptive social norms (Bicchieri, 2023)).

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BE reflects an agent's inclination to switch their behaviour, depending on their current behaviour, and ranges from 0 to 1. This means that the factors involved in the calculation of BE (BI—comprising A, N—, and PBC), as well as the resultant BE value itself, contribute to the likelihood that an agent switches their behaviour from the prior time step (e.g., 0.8 = high inclination; 0.2 = low inclination).

BE is then translated into a behaviour B by comparing the value of BE to a threshold of 0.5. If BE is lower than this threshold, the behaviour remains unchanged compared to the previous state; if it is higher, the alternative behaviour is adopted. Therefore, $B_{t=1}$ depends on the behaviour at the previous time-step $B_{t=0}$:

$$B_t = \begin{cases} 1 & \text{if } B_{t-1} = 0 \text{ and } BE_t \geq 0.5, \\ 0 & \text{if } B_{t-1} = 1 \text{ and } BE_t \geq 0.5, \\ B_{t=0} & \text{otherwise.} \end{cases} \tag{3}$$

The agents' management practice P is the value of behaviour B: If $B = 1$, the agent chooses to use CF, whereas if $B = 0$, CT is applied.

The model description of the ABM is thus structured according to these three main elements of the TPB: *Attitudes*, *Social Norms* and *Perceived Behavioural Control*.

Farmers' individual **Attitudes** (A) towards soil conservation and yield maximisation shape the evaluation of their ecological performance in terms of CY and SOC. Through LPJmL, agents have access to information about SOC and CY of their own farmlands ("cells"), as well as that of their neighbours at each time step. Following the spatial structure of the LPJmL gridcells, farmers consider the 8 gridcells adjacent to their own land, i.e., their Moore Neighbourhood of range 1, as their neighbours (Abrahart et al., 2003). Both sources of information—own farmland and neighbouring farmland—are taken into account, reflecting personal experience and social learning processes. These two components are weighted using $\omega_{A_{self}}$ and $\omega_{A_{nbr}}$ and combined in the attitude-based evaluation of the agents' current land management success.

$$A_i = \omega_{A_{self}} \cdot A_{self} + \omega_{A_{nbr}} \cdot A_{nbr} \tag{4}$$

The emphasis, and thus weights, placed on the different ecological factors (CY and SOC), as well as the influence of the different learning processes (social-ecological learning from personal experience, and social learning from neighoring farmers), are determined by the farmer's AFT. The information about SOC and CY is weighted differently using ω_{SOC} and ω_{CY}, while the importance of the learning processes is captured by $\omega_{A_{self}}$ and $\omega_{A_{nbr}}$.

In the process of evaluating one's own land (A_{self}), the farmer compares the current yield (CY_t) and soil values (SOC_t) to the values they observed the last time they used the alternative strategy (CY_{t-p}, SOC_{t-p}) (e.g., "*6 years ago, I switched from conventional farming to conservation tillage. Now I want to evaluate if my switch positively influenced my soil health. Compared to to before I switched, my soil organic carbon values are very high, my soil is healthier, so I am inclined to continue with conservation tillage*"). In cases when farmer agents have never switched strategy, they compare the current value to the value of the last timestep (e.g., "*I've always been practising CT, but my yields decline.*").

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$A_{self,t}$ is calculated using a sigmoidal normalisation function

$$A_{self,t} = sigmoid\left(\omega_{CY} \cdot (\frac{CY_{t-p}}{CY_t} - 1) + \omega_{SOC} \cdot (\frac{SOC_{t-p}}{SOC_t} - 1)\right), \tag{5}$$

where

$$CY_{i,tP} = CY_{i,\tau}, \quad \tau = \max\{\tilde{t} < t \mid P_{i,\tilde{t}} \neq P_{i,t}\}, \tag{6}$$

and

$$SOC_{i,tP} = SOC_{i,\tau}, \quad \tau = \max\{\tilde{t} < t \mid P_{i,\tilde{t}} \neq P_{i,t}\}, \tag{7}$$

and

$$sigmoid = 0.5 \cdot (\tanh(x) + 1). \tag{8}$$

In the process of comparing one's own strategy's success to neighbours (A_{nbr}), farmer agents i evaluate their own performance (in terms of CY and SOC) in comparison to the success of neighbours employing a different strategy ($P_i \neq P_j$) (e.g., "*I practice conventional farming. In comparison to my neighbours practising conservation tillage, my soil quality is very poor. As I have a positive attitude towards soil conservation, I am more inclined to switch to conservation tillage, as this seems to be a promising strategy to improve soil health*"):

$$A_{nbr,t} = sigmoid\left(\omega_{CY} \cdot (\frac{< CY_{nbr} >}{CY_{i,t}} - 1) + \omega_{SOC} \cdot (\frac{< SOC_{nbr} >}{SOC_{i,t}} - 1)\right), \tag{9}$$

where

$$sigmoid = 0.5 \cdot (\tanh(x) + 1). \tag{10}$$

This component depends on the agents' neighbours' farming outcomes CY_{nbr} and SOC_{nbr}, and their means, $< CY_{nbr} >$ and $< SOC_{nbr} >$. The comparison of own and neighboring performance is based on the evaluations of both factors at the current time-step:

$$< CY_{nbr} > = \begin{cases} \frac{1}{n} \cdot \sum_{j=1}^{n} CY(j), & P_i \neq P_j \\ 0, & P_i = P_j \end{cases}, \tag{11}$$

and

$$< SOC_{nbr} > = \begin{cases} \frac{1}{n} \cdot \sum_{i=1}^{n} SOC(j), & P_i \neq P_j \\ 0, & P_i = P_j \end{cases}. \tag{12}$$

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Taken together, these two comparison processes form the attitude-based evaluation of the inclination to stay with the currently practised management style or switch to a different one. Each year, individual farmers thus receive information on yield quantity and soil quality, which they use slightly differently in the two attitude sub-components. In both evaluation sub-components (own land and social learning), farmer agents obtain ecological information (e.g., "*Under current conventional management, my yields are good, but my soil quality is rather poor*"), and evaluate this information on the basis of their own attitude (e.g., "*I am a* pioneer *agent, and have a positive attitude towards soil health, so I weight the information on soil quality more strongly as compared to yield quantity*").

However, the two learning processes also exhibit slight differences: In the "learning from one's own land" sub-component, farmers evaluate their own performance over a period of time. This sub-component therefore incentivises switching to a different strategy if the currently practised one is evaluated as performing badly, without considering how the other strategy might perform. The social learning sub-component functions in a slightly different way: here, performance is not compared over time, but instead across practices at the current point in time. If a farmer agent practices CF, they compare their performance to neighbours using a different strategy, such as CT. If that comparison yields an observed advantage of the other strategy, this adds to the farmer's inclination to switch to that particular strategy. Finally, both the strategy-switch inclination from social learning that is directed at a specific different strategy, as well as the inclination to try out a different strategy due to dissatisfaction with one's current performance, are integrated to form a value representing the individual attitude in the TPB.

Subjective norms (N), which describe social pressures encountered by an individual (Ajzen, 1985), are captured as descriptive social norms informed by a farmer's observations of their neighbours' land-use styles. There is strong evidence suggesting the influence of social norms, which may be related to geographical proximity (neighbouring farms) or membership in certain groups, associations, or communities of practice, on the adoption of farming practices (Brown et al., 2018; Swart et al., 2023). Unlike the social learning process that involves performance comparison, the social norms considered here influence decision-making by signalling the majority behaviour of a reference group. Both the current local descriptive social norm and its strength are considered in decision-making—the stronger the social norm, the higher the norm's influence. For example, if a farmer currently practices CT and all of their neighbouring farmers practice CF, the norm component's contribution to the BE, and thus to a potential strategy switch, is larger compared to a case when only a slight majority (e.g., 5 out of 8 neighbours) practice CF. In each timestep, the prevalent social norm N is evaluated by accounting for the dominant behaviour B_{nbr} of the agent's neighbors n in the following way:

$$N_i = \begin{cases} 0.5 \cdot (\tanh(0.5 - < B_{nbr} >) + 1), & B_{i,t-1} = 1 \\ 0.5 \cdot (\tanh(< B_{nbr} > - 0.5) + 1), & B_{i,t-1} \neq 1 \end{cases}, \tag{13}$$

where

$$< B_{nbr} > = \frac{1}{n} \cdot \sum_{j=1}^{n} B(j). \tag{14}$$

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Both Attitudes and Norms are dynamically and endogenously evaluated in each timestep of the model. In contrast, the initial value of **Perceived Behavioural Control** (PBC) is set during model configuration according to AFT, with the *pioneer* AFT receiving a higher PBC value than the *traditionalist* AFT. PBC influences the "translation" of behavioural intention into behaviour: if the PBC value is large, this process of acting out one's behavioural intentions, and potentially changing behaviour, is supported. The smaller the PBC value, the more inertia is introduced, which significantly reduces the likelihood of behavioural change.

In our model conceptualization, we assume that after a management strategy switch (either from CF to CT or vice versa) has occurred, PBC is reduced by 0.25, until a minimal PBC threshold of 0.5 is reached, making a further switch less likely. This reflects the observation that a switch of agricultural management strategy is a significant decision for a farmer and their operations—a step that is often connected to investments for novel machinery, training, etc., thereby inducing a certain path dependency (Rønningen et al., 2021; Song et al., 2022). When the reduction of PBC reaches the minimal threshold, the inhibiting effect on translating intention into behaviour becomes so large that strategy switches are nearly completely prevented. In cases where farmers show strong intention to switch but are inhibited by low PBC, PBC is incrementally raised for the next timestep.

$$PBC_i = \begin{cases} \max(PBC_{i,t-1} - 0.25, 0.5) & BE_i > 0.5 \\ \min(PBC_{i,t-1} + \frac{0.25}{t_s}, 1) & 0.4 < BE_i \leq 0.5 \end{cases} \quad (15)$$

Agent functional types

In this model version, we introduce two farmer AFTs. The AFT concept was first introduced by Arneth et al. (2014) in analogy to the Plant Functional Types (PFTs) used in DGVMs like LPJmL. It serves as an approach to develop generic agent types to simulate up to global social-ecological, behavioural land-use ABMs. AFTs are based on the primary characteristics of roles (such as farmer, forester, or extensionist agent) and cognitive as well as behavioural processes (such as attitude formation, learning, imitation). Agent heterogeneity, implemented through concepts like AFTs, is an important frontier for (land-use) ABMs, especially regarding large-scale applications (Rounsevell et al., 2014).

The InSEEDS model, in its current version, involves two AFTs with the role "farmer", who differ in the way they weight different factors in their cognitive-behavioural processes: *traditionalist* farmers and *pioneer* farmers.

The distinction of different farmer AFTs is rooted in the facts that (a) land-use priorities and decision-making vary among different farmers (e.g., possible variation in different climate zones, socio-cultural environments, farm sizes and purposes, etc.) (Edwards-Jones, 2006; Singh et al., 2016), and consequently (b) transition pathways for those different groups will be distinct (Maybery et al., 2005; Stringer et al., 2020).

Many different farmer typologies exist (Burton and Wilson, 2006; Malek et al., 2019; Bartkowski et al., 2022). In the context of applying conservation agriculture practices like CT, Casagrande et al. (2016), for example, describe the farmer type "soil conservationist" to be mainly motivated by soil preservation and minimising environmental impacts. In addition to "pure environmental conservation" aspects, this focus on soil health can be interpreted as a more future-looking perspective: investing in soil health can support the provision of stable yields in the longer run. This farmer type, additionally, was found to be "less concerned than other groups by problems, showing their enthusiasm for conservation agriculture" (Casagrande et al., 2016, p. 293). This conviction to improve soil quality can be mapped to (1) the emphasis on their own attitude and values as compared to the social norm, and (2) the relative importance of SOC as compared to CY parameters in our *pioneer* AFT. Comparing the two learning processes and the resulting attitude sub-components, A_{nbr} is given more importance and thus a higher $\omega_{A_{nbr}}$ in the case of *pioneers*. In contrast to mere normative pressure, they are expected to be considerably influenced by social learning opportunities, and learn from their neighbours' successes and failures using a different management strategy to compare their performance with their own. This can, for example, be linked to the empirical finding that *pioneer*-type farmers have strong social networks they rely on for information-seeking (Casagrande et al., 2016). We additionally conceptualise this AFT to possess relatively high perceived behavioural control: in line with their high levels of individual knowledge, and low consideration of agronomic problems, this AFT has a high belief about being capable of putting their intentions into practice. With regard to non-farmer-specific strands of literature, this combination of AFT attributes can also be connected to the concepts of "innovators" and "early adopters" (Rogers, 1962) and "trendsetters" (Bicchieri and Funcke, 2018). Social science research shows that certain sub-groups or individuals tend to abandon predominant descriptive social norms and spearhead change, well before a descriptive norm tipping point is reached. The willingness to defy from a dominant social norm has also been associated with high levels of self-efficacy (the belief that one is capable to influence events), and lower risk perception (Bandura, 1993; Bicchieri and Funcke, 2018). Self-efficacy, and low risk perception can be regarded as important components of PBC, which is why, in our *pioneer* AFT, a relatively low consideration of social norm is coupled to a relatively high PBC, as compared to the *traditionalist* AFT.

Casagrande et al. (2016) sketch another farmer type, motivated mainly by agronomic problems and challenges, and strongly reliant on their neighbours for advice. These behavioural factors can be connected to the *traditionalist* AFT, who places a stronger emphasis on yields as compared to soil health. The emphasis on short-term yield maximisation can be interpreted as a reflection of temporal discounting (Chapman, 1996), or temporal myopia (van der Wal et al., 2018). They also rely more strongly on social norms as compared to their own attitude than the *pioneer* AFT. This means that, in comparison to the *pioneer* AFT, the *traditionalist* AFT would be more reluctant to adopt a novel management practice that is not well-established yet. In contrast to the *pioneer* AFT, the *traditionalist* AFT is conceptualised to have a higher risk aversion and be more sensitive to risk in general (Casagrande et al., 2016), which is translated into a lower PBC and therefore a more pronounced intention-behaviour gap. Regarding the two learning processes, *traditionalists* are expected to rely less on information obtained through social learning processes, and instead rely more on observing their own land. The initial PBC value of the *traditionalist* AFT is set to be lower as compared to the *pioneer* AFT.

In the model implementation, these two farmer types are distinguished by different weights applied to decision-making parameters, which will be laid out in more detail in Chapter 3.1.

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3 Simulation experiments with the InSEEDS model

3.1 Model parametrisation

The two AFTs we introduce in the InSEEDS model are parametrised differently according to their distinct roles and characteristics. The default values highlighted in Figure 3 and Table 1 are selected as a result of the sensitivity analysis shown in figure 4.1. The share of the two different AFTs in a simulation run is determined by parameter S, which reflects the share of *pioneers* in a simulation run. Concurrently, the share of *traditionalists* amounts to $1 - S$. For each cell, the type of agent is determined probabilistically using a Bernoulli trial with the aforementioned probabilities for a cell being assigned a *pioneer* (S) or *traditionalist* ($1 - S$) AFT.

Parameter Name (Short Form)	Weight Variable	Short Form	Traditionalist	Pioneer
Perceived Behavioural Control (PBC)	pbc	PBC	0.75	0.95
Attitude (A)	weight_attitude	ω_A	0.6	0.8
Crop Yield (CY)	weight_yield	ω_{CY}	0.8	0.4
Soil Organic Carbon (SOC)	weight_soil	ω_{SOC}	0.4	0.8
Social Norm (N)	weight_norm	ω_N	0.4	0.2
Attitudes from Social Learning (A_{nbr})	weight_social_learning	$\omega_{A_{nbr}}$	0.4	0.6
Attitudes from Learning from own Land (A_{self})	weight_own_land	$\omega_{A_{self}}$	0.6	0.4

Table 1. AFT parameter values for *traditionalist* and *pioneer* AFTs.

Most of the exact parameter values needed to calculate the decision making, i.e., the weights of N or A, cannot be based on quantitative empirical data, yet, due to a lack of such datasets for the parametrisation of the human component in World-Earth models (Arneth et al., 2014). Some of the parameters, like SOC and CY, $attitude\_own\_land$ and $attitude\_neighbors$, and $norm$ and $attitude$, are weighted in relation to each other on the basis of the qualitative differentiation between AFTs: while the precise weights' parameter values are not derived from quantitative empirical data, their parameter ranges (e.g., own attitudes are weighted higher than social norms in the *pioneer* AFT as compared to the *traditionalist* AFT) are based on qualitative AFT differences that can be found in the literature (see Chapter 2.2).

3.2 Simulation experiments and simulation protocol overview

The following global simulation runs were performed for the sensitivity analysis and result generation: (1) The base run using the standard parametrisation laid out in Table 1. This is run is the foundation for the results presented in section 4.2. (2) 30 additional sensitivity runs, as shown in table 2, systematically varying (sets of) parameters within the decision-making function, as shown in figure 3. (3) 6 further runs varying the initial share of AFTs using the baseline run configuration (Table 1). The sensitivity analysis procedure is further elaborated on in following subchapter 3.3.

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Through its embedding in the copan:LPJmL framework, InSEEDS simulation runs rely on the initialisation and spin-up of the LPJmL model. This requires an LPJmL spin-up simulation of the natural vegetation as well as the land use (Schaphoff et al., 2018) until the year 1901. It is followed by a historical simulation period from 1901 to 2022 using historical climate input data from ISIMIP3a (Lange et al., 2023). Land-use as well as fertiliser and manure inputs are obtained and used from Ostberg et al. (2023) while data on residue management was applied from Dietrich et al. (2020). A dataset for tillage was created by Porwollik et al. (2019), which provides temporally and spatially explicit data on the global distribution of conservation agriculture practices until 2010, after which the data is kept constant until the end of the simulation in 2022. Behaviour, in terms of CF and CT practices, is thus initialised by starting this global gridded data set on the spread of CA. Since CT is a subset of CA, the spread of CT in year 2022 is assumed to represent but underestimate the actual uptake of CT practices in the start year 2023 of the InSEEDS simulation.

These LPJmL spinup simulations serve as the basis for InSEEDS simulations: Starting in the year 2023, LPJmL ceases to run as a stand-alone model, and is bidirectionally coupled with the ABM component through the copan:LPJmL framework. The integration of LPJmL as an environmental (ENV) and an ABM as a socio-cultural and socio-metabolic (CUL & MET) component yields the InSEEDS model. The coupled simulation is run until the year 2100. The climate is kept constant until the end of the simulation to exclude any climate-change feedbacks and to focus solely on the interactions between humans and the biosphere.

3.3 Sensitivity analysis

Given the qualitative approach to parametrising the AFTs sketched in subsection 3.1, the subsequently presented results of the sensitivity analysis should be understood as demonstrating the dynamical interplay of the underlying parameters in order to validate the overall model behaviour and explore different model pathways, instead of quantitative insights based on a precise real-world model parametrisation. To achieve this, a sensitivity analysis (SA) was conducted. This consists of (1) the variation of the initial AFT share, as well as (2) the variation of parameters in the decision-making function.

The AFT share was varied in 20% increments, ranging from a 0% *pioneer* (100% *traditionalist*), to a 100% *pioneer* (0 % *traditionalist*) setup, using the base run configuration for the decision-making function parameters.

The decision-making function's sensitivity was tested by varying each underlying parameter of BI within equal intervals across realistic ranges. Taken together, Figure 3 and Table 2 provide an overview of the experiments conducted for the SA. Table 2 provides an overview of all simulation runs conducted for the SA. The "Experiment" column shows which parameter(s) were altered, while all other parameters were kept in the base run configuration (Table 1). In case of the first three experiments, (1) ω_A & ω_N, (2) $\omega_{A_{self}}$ & $\omega_{A_{nbr}}$, and (3) ω_{SOC} & ω_{CY}, weights are varied in a pairwise fashion, reflecting aforementioned interdependencies between these values. Figure 3 visually illustrates this interdependence: the green middle row captures the runs conducted in experiment (1) ω_A & ω_N. We can see that the default values in simulation run 1 in this experiment (bold gray circling) of the *traditionalist* agents (solid coloured bars) lie at 0.4 for ω_N and 0.6 for ω_A. When ω_N is lowered to 0.2 in this experiment, correspondingly, ω_A is raised to 0.8 for simulation run 0.

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The same principle applies to the weight of *social learning* and *learning from one's own land*, as well as the weighing of *yield* and *soil*, within the attitude component. The aforementioned differences between the two AFTs are accounted for in the sensitivity analysis. The sensitivity of the weights of the TPB (ω) are shown in Figure 3 and elaborated on in the results Chapter 4.1 on parameter sensitivity. The "Pioneer AFT difference" column lists how the basic parametrisation differs across the two AFTs with reference to the standard configuration value: For example the *pioneer* AFT's ω_A is 0.2 higher than the *traditionalist's* ω_A (+0.2), while, due to the coupling of these values, the *pioneer's* ω_N is 0.2 lower than the *traditionalist's* ω_N (-0,2). In Figure 3 this difference is reflected in the different allocation of the hatched, *pioneer* AFT, and the solid *traditionalist* bars. Again using the example of the ω_A & ω_N experiment, the baseline value (run 1, bold gray circled) for ω_N of the *pioneer* AFT lies at 0.4, while the associated *traditionalist's* value lies at 0.6.

Experiment	Simulations	Parameter	Pioneer AFT difference	Step	Value range	Unit
ω_A & ω_N	4	ω_A (ω_N)	+0.2 (-0.2)	0.2	0 - 1	-
$\omega_{A_{self}}$ & $\omega_{A_{nbr}}$	4	$\omega_{A_{self}}$ ($\omega_{A_{nbr}}$)	-0.05 (+0.05)	0.05	0 - 1	-
ω_{SOC} & ω_{CY}	4	$\omega_{A_{self}}$ ($\omega_{A_{nbr}}$)	+0.2 (-0.2)	0.2	0 - 1	-
PBC	6	PBC	+0.2 (-0.2)	0.2	0 - 1	Year
Pioneer share S	6	pioneer_share	-	0.25	0 - 1	-

Table 2. Simulation experiments with InSEEDS.

4 Results

The results section first lays out an analysis of the parameter sensitivity results, to then introduce findings regarding the co-evolutionary model dynamics.

4.1 Parameter sensitivity

The InSEEDS model system was run for a period of 78 years, starting in 2023 and ending in 2100. Its results for different parametrisation sets, as explained in Figure 3 and Table 2, are shown in the following. The effect of the pairwise variation of the named parameters on both biophysical (i.e., SOC and CY) and social (i.e., spreading extend of RA practices) variables is shown in Figure 4.

We can observe that the variation of the norms and attitude weights (green) has the strongest impact on the simulation results – varying this weight produces the most significant difference in simulation results, especially considering the distinction of run intention_0 on the one side, and run intention_2 to intention_4 on the other side. The lowest social norms, and, correspondingly, the highest attitude weight in run intention_0, yield the maximum share of RA practitioners, and the highest SOC and CY levels in the year 2100 across all parameter configurations. Vice versa, all runs with a higher weighting of norms and, consequently, lower weighting of attitude, (intention_2 to intention_4) result in the lowest share of CT adoption, and the

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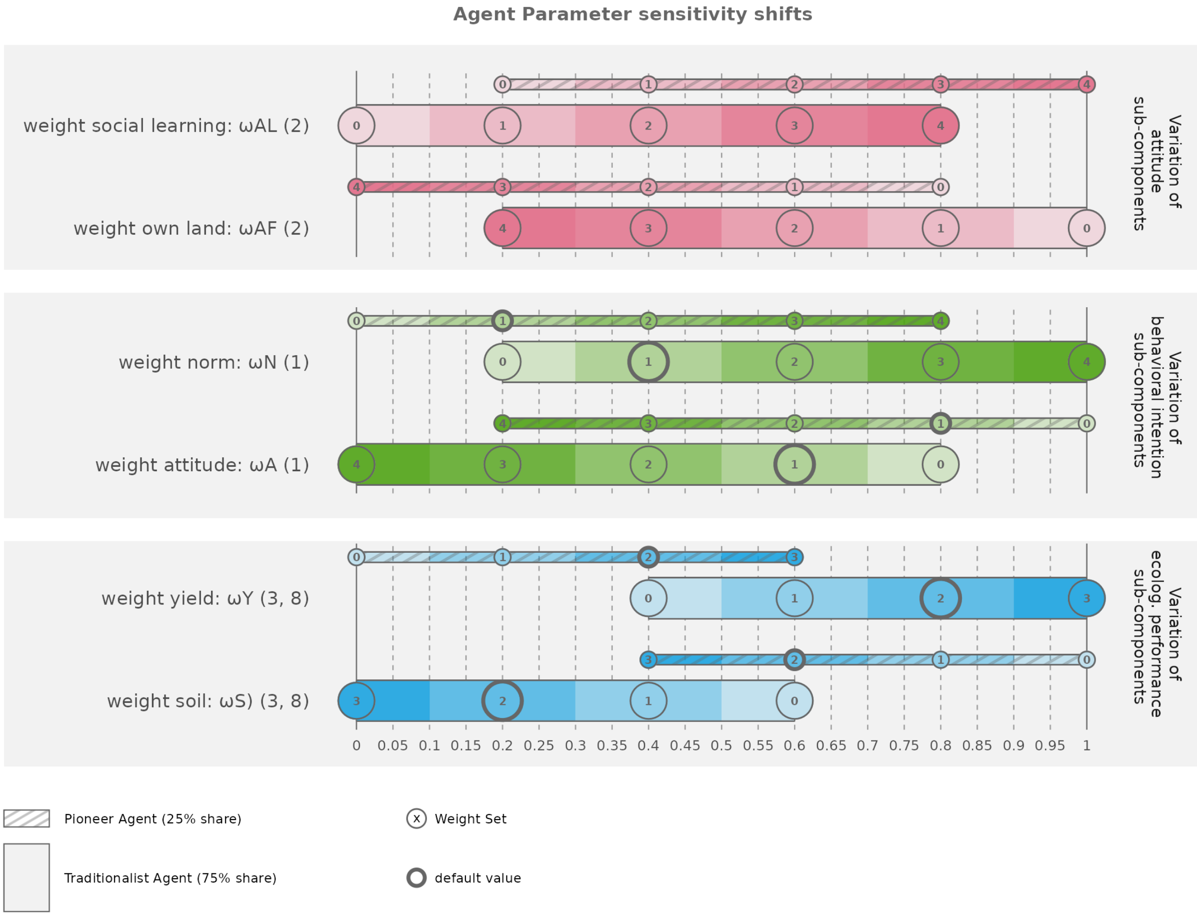

Figure 3. TPB weights (ω) that have been shifted along equal intervals within realistic ranges. There are 3 sets with each two ω for each different level of the TPB equation: (1) the variation of attitude and norm as the sub-components of behavioural intention (green), (2) the variation of social learning and learning from one's own land as the sub-components of attitude (pink), and (3) the variation of soil and yield as factors in both learning processes (blue). ω intervals are highlighted for *traditionalists* (solid bard) as well as for *pioneers* (hatched bars).

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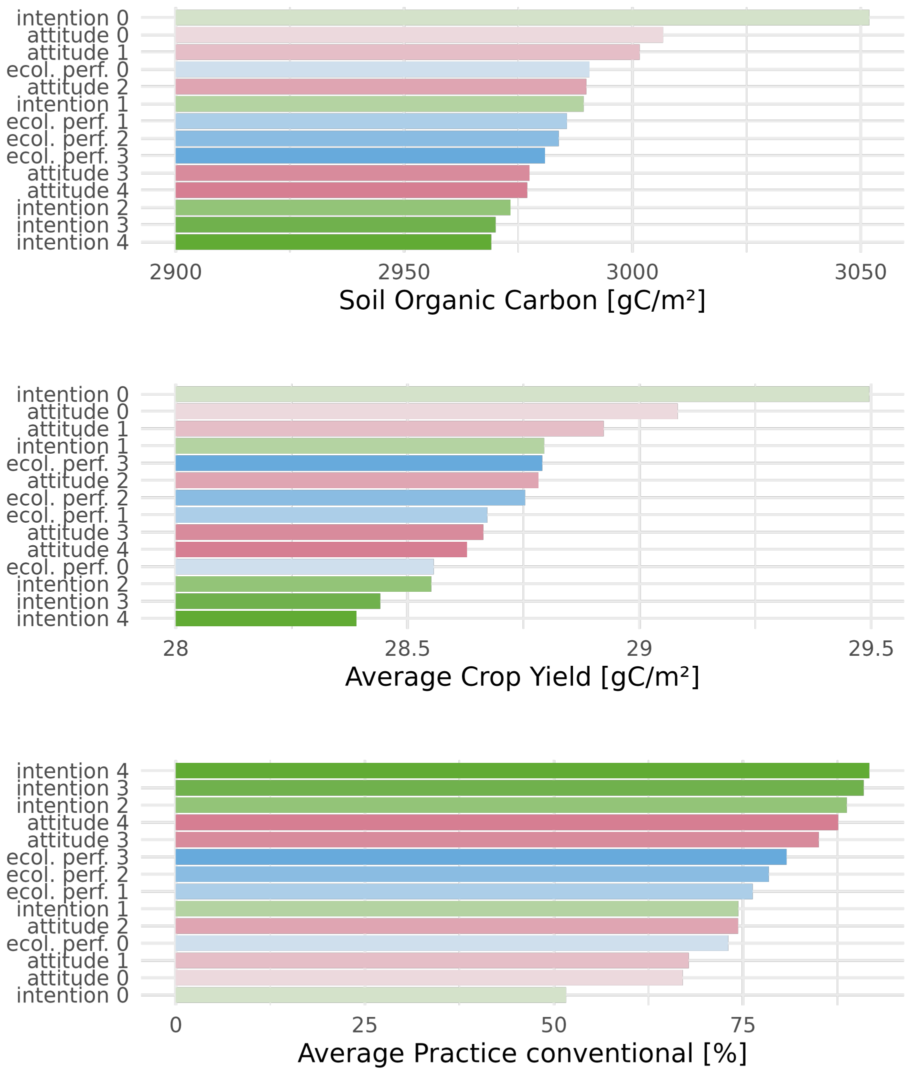

Figure 4. Global analysis of the impacts that parameter variations have on different model variables after a simulation run (year 2100). The parameter values of the depicted runs can be mapped to the colour scheme introduced in Figure **??**. The blue runs depict a variation of the weighting of SOC and CY in the learning sub-components of attitude formation. The darker the blue, the higher CY, as opposed to SOC, is weighted in the ecological evaluations performed by the farmers. The pink runs depict a variation of the weights attributed to social learning, and the observation of the agents' own land, which together form the attitude component. The darker the pink, the higher social learning, as opposed to the evaluation of the agent's own land, is weighted. The green runs depict a variation of the weights of social norm and attitude, which, taken together, form the agents' behavioural intention. The darker the green, the higher social norms, as opposed to the farmers' own attitude, is weighted.

lowest levels of CY as well as SOC in 2100. With parameter configurations placing only minimal emphasis on social norms, the attitude component, that considers the evaluation of ecological performance through social learning and the observation of one's own land, is dominant in the decision-making function.

The weighing of social learning and observing and learning from the dynamics present at the agent's own land, which together form the attitude sub-component, has the second largest influence on model dynamics (attitude_0-4). Here, the results show the large influence that the observation of one's own land has as compared to social learning. The more emphasis is placed on learning from one's own land compared to social learning, the higher the levels of SOC and CY, and the larger the share of CT adopters in simulations until 2100.

The weighting of yield and soil (ecol_perf_0-3) in the decision-making function results in the least pronounced global effects. Still, a general pattern is observable: The higher SOC, as opposed to CY, is weighted, the larger the share of CT adopters and the higher the levels of SOC. CY levels are highest when CY is weighted most strongly, as opposed to SOC.

Regarding sensitivity to factors outside of the decision-making function, the sensitivity analysis shows that the model is highly sensitive to the initial share of AFTs. Comparing the two extreme scenarios of (a) 0% and (b)100% *pioneer* share, we find that especially social outcomes vary decisively: The full pioneer share scenario (a) yields a 50% higher adoption rate of CT, as compared to scenario (b). Regarding ecological outcomes, the difference is less pronounced, with 2% higher SOC and CY levels of scenario (a) as compared to (b). All three indicators (adoption of CT, levels of SOC and CY) increase steadily with the share of *pioneers*.

4.2 Coupled, co-evolutionary model dynamics across scales

The adoption of CT or CF practices, and therefore, the spatiotemporally resolved spreading dynamics of these practices can be analysed and illustrated from cell to up-to-planetary scales. The copan:LPJmL model framework description paper (Breier et al., in prep) – companion paper to this publication – focuses on possibilities of global spreading analyses. Here, we want to dive further into more nuanced dimensions of the co-evolutionary dynamics, which can more easily be observed by zooming into results on smaller spatial scales.

4.2.1 National scale

Applying a default parametrisation (Table 1), the coupled model interactions with focus on the main variables, behaviour, SOC and CY are shown for three different countries, as extracts of the global simulation (Breier et al., in prep) in Figure 5. The chosen countries, respectively, showcase interesting model dynamics. Figure 5 (a) shows the farming behaviour from 2022 to 2100. The most lightly coloured cells represent those that have not changed their management since year 2022. Figure 5 (b) and (c) show the ecological impacts the behaviour has on SOC and CY, respectively.

In some areas, the importance of local networks and connections for adoption and spreading becomes evident. In these cases, one can observe "seeds" of new management practices that spread to adjacent cells, and sometimes evolve into a new shared management cell cluster, over the simulation period. Here, the principal of local spreading comes into play, which is influenced both by social norm and social learning dynamics: the local descriptive social norm encourages the adoption of locally (i.e.,

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in an agent's 8 neighbouring cells) dominant behaviour; a mechanism that functions irrespective of ecological performance. Regarding social learning, agents weigh in the performance of their neighbours with the opposed management strategy – the better the neighbours that use a different management strategy's ecological performance, the more likely the adoption of that very strategy (eq. 9). These effects can be observed in parts of southern Spain, as well as South Africa (close to Bloemfontein), where colour gradients around a seed indicate successful local management practice spreading (see purple boxes).

In other areas, the adoption of novel practices happens without geographical proximity to these practices (see pink boxes). One such example can be found in South America: on the Paraguayan map, also adjacent countries are visible, and we can see part of Brazil at the eastern border of Paraguay. Here, in the northern section of the map (close to Corumbá), we can observe a switch from CT to CF that took place despite a lack of CF being practised in the neighbourhood of the respective cell. The same dynamic, albeit the other directionality, can be observed on the Balearic Islands, Spain, as well as the area around the coastal city Durban, South Africa (pink boxes). In these cases, the importance of attitude-formation based on observing one's own land becomes evident. Without neighbours practising different management to learn from, or local social norms to exert pressure, a switch in decision-making can solely arise from a dissatisfaction with the agent's own ecological performance.

In the analysis of simulation results, it becomes evident that model behaviour differs significantly across different world regions and their respective conditions. In the ecological realm, distinct biophysical conditions in the different geographical areas play a central role in the evaluation of the biophysical performance (de)merits that a certain management practice entails. This performance is measured by the direction of the impact the practice has on both biophysical variables, SOC and CY. The effect on both variables are shown in Figure 5 (b, c).

While, on a global average, we can observe that CT, as compared to CF, has a positive effect on SOC and CY, the bio-physical, and thus also social-ecological dynamics differ considerably between and within countries: In southern Spain as well as parts of South Africa, we can, for example, observe an overall positive impact of the switch to CT on SOC as well as CY. Nevertheless, especially in Paraguay, very different dynamics can be observed: Irrespective of the management practice chosen, a general trend towards a loss of SOC and CY becomes evident here. As pointed out in Chapter 2.1, the biophysical model behaviour in Paraguay can be explained by land-use change legacy effects also described in Herzfeld et al. (2021). Simulation results reflect these legacy effect in the form of a continuous decrease of SOC, irrespective of the management practice, as compared to the pre-agricultural-land-conversion state. Some cells in the centre of Paraguay even show missing data points regarding SOC values. These different ecological preconditions, legacies, and therefore the ecological impact of the given management options also influence the decision-making and, in turn, spreading dynamics.

In addition to ecological heterogeneity, social heterogeneity greatly influences model dynamics. The initial share of the two AFTs has been shown to largely impact simulation dynamics and model results. A systematic comparison of different initial AFT shares, for example, shows that the global mean behaviour change differs by up to 60 % between scenarios with only *traditionalist*, or only *pioneer* AFTs.

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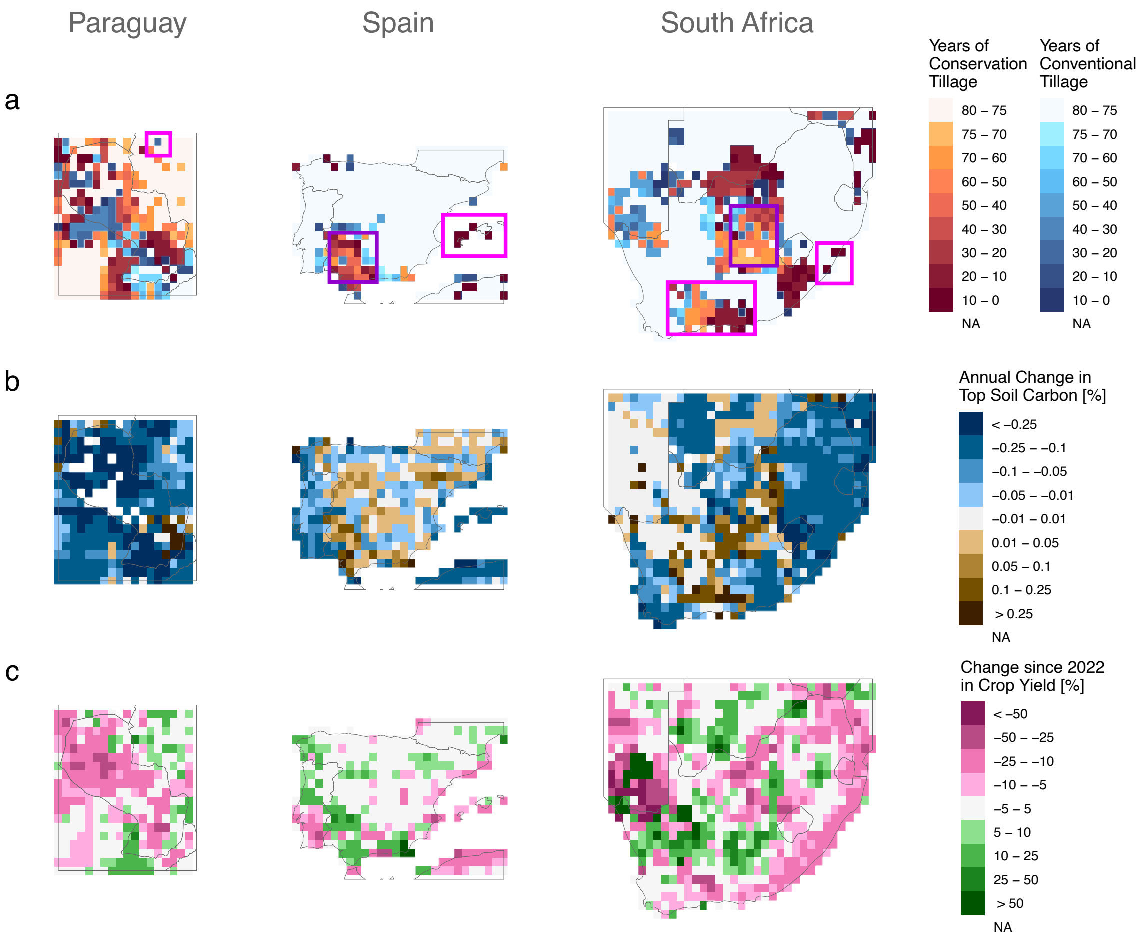

Figure 5. InSEEDS simulation of year 2100 for selected countries Paraguay, Spain and South Africa. *a* shows the age of the applied management (CF/CT) and behaviour change since start of the coupled simulation (2022) –the lighter the shade, the more recent the adoption. *b* shows the annual change rate of the top soil carbon layer (20 cm), and *c* the change of the CY since 2022. Adoption of a novel practice that isn't driven by the local social network are marked in pink, illustrations of local spreading processes are marked in purple, and the distinct ecologically heterogeneous conditions are marked in red.

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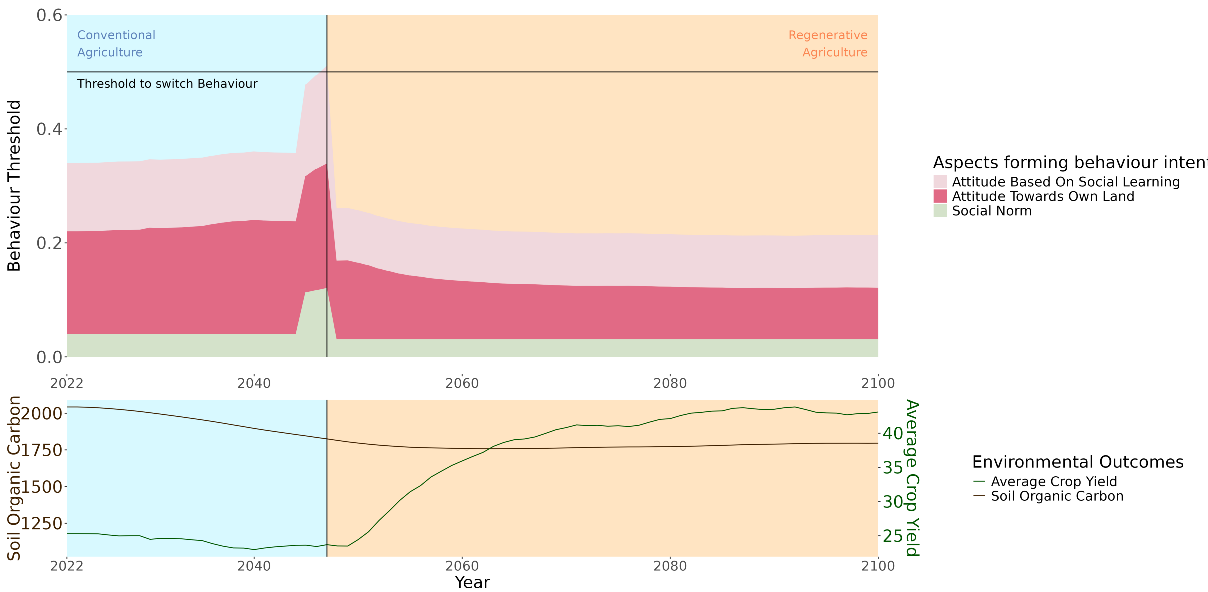

Figure 6. Depiction of the decision-making dynamics underpinning a norm-dominated switch from CF to RA, including the behavioural, social-ecological, and ecological dynamics in cell 26735.

4.2.2 Local / cell scale

On the level of one cell, we can observe further dynamics related to different dimensions of the decision-making function, like norms and attitude. The cells were chosen for several reasons: (1) they exhibit particularly interesting, and distinct mechanisms leading up to the switch of the farmer management practice, (2) they are located at the Balearic Islands (see the marked islands on Figure 5), and their particular properties as island cells limit the influences acting on them, and thus makes them more easily traceable. The runs stem from experiments conducted in the sensitivity analysis, and correspond to the intention_0 run parametrisation (see lightest green configuration in Figure 3). The parametrisation yields a slightly higher valuing of attitudes, and slightly lower weighting of social norms, as compared to the base run configuration (see Table 1).

Zooming into single model runs in distinct cells, we can observe different dynamics leading up to a switch from CF to CT, as well as the switch's consequences. The two illustrations 6, 7 depict the translation of behavioural expectation into behaviour at the threshold of 0.5 (see 2.2). The two attitude sub-components are shown in pink (light pink: attitude based on social learning, dark pink: attitude based on learning from own land), the norm component is depicted in light green. As described in Section 2.2, these components add up to the behavioural expectation BE. In the displayed figure, these values already factor in the effect of PBC on attitude and norm.

In cell 26735, only a slight increase of the attitude-based inclination to switch from conventional (blue) to regenerative (orange) agriculture between the years 2022 and 2040 is visible. This can be attributed to the overall worsening trend of ecological performance in this period: SOC and CY levels decrease over this period. The impulse to switch strategy, in this

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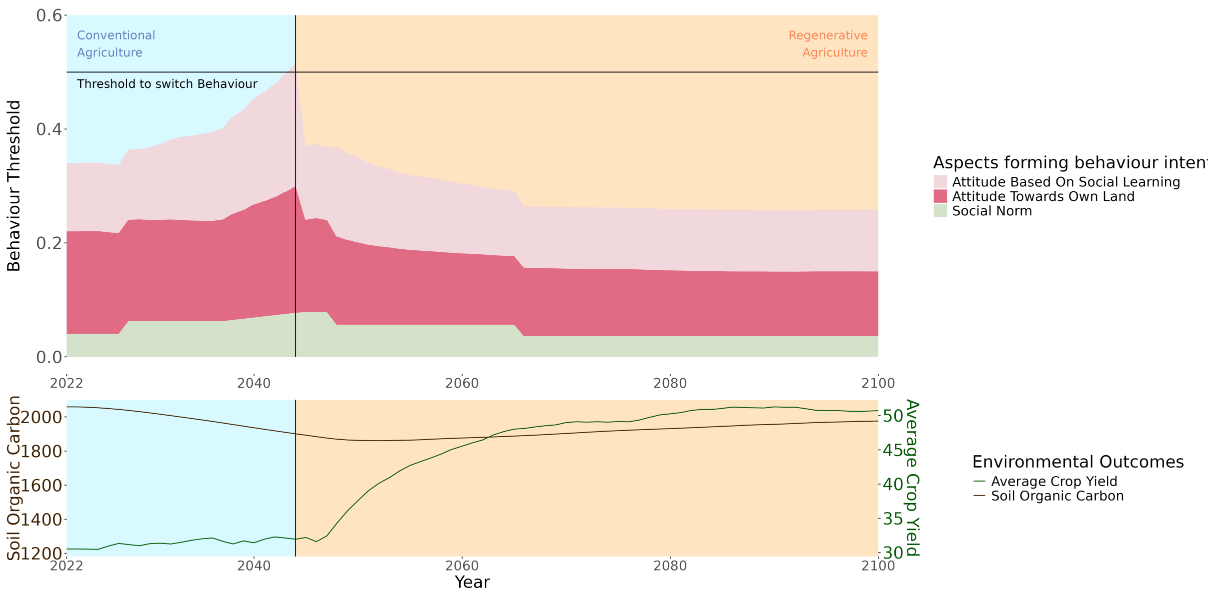

Figure 7. Depiction of the decision-making dynamics underpinning an attitude-dominated switch from CF to RA, including the behavioural, social-ecological, and ecological dynamics in cell 26653.

run, is provided by a peak in social norms ca. 2042, which points to a neighbouring cell recently having undergone a switch to RA. Together with the already relatively high attitude-based inclination, this norm-based inclination to switch pushes BE over the threshold of 0.5 and the agent to adopt RA instead of CF in the late 2040s. Right after the switch, we can observe changes in the biophysical model variables: a steep increase, and stabilisation at high levels, of CY becomes evident. While the SOC levels don't improve immediately, the previous downwards trend gradually stops, SOC levels stabilise in around 2060 and even slightly increase towards the end of the century. This improvement of ecological performance, especially yields, renders the attitude-based inclination to switch back to CF smaller than at any prior point in time: the farmer agent is content with their ecological performance and not inclined to change their management.

In contrast to this norm-induced switch, the agent's switch to RA in cell 26653 is clearly driven by changing attitudes, especially resulting from social learning processes (light pink colour in Figure 7). In the mid-2020s, we see a slight increase in the social norm values, again pointing to an adoption of RA in the agent's neighbourhood. Following this increase, the "attitude based on social learning" value increases steadily (and by a higher magnitude than the "attitude own land" sub-component). The adoption of RA in the neighbourhood (that can be observed in the cell's social norm sub-component changing) is thus followed by a process of learning from that very example. As the outcome of that learning process is a growing inclination to switch to RA, we can infer that the neighbouring newly adopted RA management was evaluated to be successful ecologically. Ecological performance improves analogously to the previous run, which is why the inclination to switch back to CF shrinks and stabilises at a low level after RA was adopted.

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In both cells, we can additionally observe the impact that the adaptive formulation of PBC has on decision-making dynamics. As described in eq. 15, we assume that with repeated decision-making evaluations close to the threshold for switching, agents gradually increase their PBC. The increase of PBC, in turn, decreases the intention-behaviour gap, and supports acting out the norm- and attitude-based behavioural intention (BI) of the farmer. For example, in Figure 7, this process is reflected in the increase of all three decision-making sub-components (best seen in the “attitude based on social learning" sub-component) starting in the mid-2030s, when the cumulative inclination to switch (BE) crosses the behavioural threshold of 0.4.

5 Discussion

In this paper, we have introduced the InSEEDS model, described its social, ecological components, and their interactions, and tested the model’s parameter sensitivity. We laid out first simulation results that point to distinct centrally important elements and processes in the co-evolutionary model dynamics. We zoom into certain dimensions of the co-evolutionary dynamics that can be observed at different spatial scales of simulation results, from global to cell level.

The InSEEDS model constitutes a significant methodological and conceptual advancement in the realm of World-Earth simulations. As the first model to fully integrate agent-based social processes with a state-of-the-art DGVM, InSEEDS provides a unique platform for exploring the co-evolutionary feedbacks between human decision-making and biophysical land system dynamics at scales ranging from local to planetary. While previous modelling efforts have typically focused either on the biophysical or the social domain, have utilized stylized representations of human actors, or have been limited to small spatial scales, InSEEDS bridges this gap by explicitly capturing the dynamic interplay between heterogeneous farmer behaviours, social networks, and ecological processes. The modular and expandable design of InSEEDS enables researchers to incorporate multiple types of agents, learning mechanisms, and agricultural management practices, thereby accommodating some of the complex realities of agricultural systems in the Anthropocene.

Notably, InSEEDS uniquely enables the examination of how social norms, attitudes, and learning —not only from one’s own experience but also from neighbours— drive the adoption and spread of regenerative land management practices in heterogeneous environments. This capacity to simulate the emergence of large-scale systemic transitions from individual and network-level processes opens new opportunities for analysing resilience, tipping points, and leverage points in land-use transitions. By explicitly closing the social-ecological feedback loop between a standalone DGVM and an agent-based model component, InSEEDS sets an important precedent for the next generation of integrated human-Earth system models. As such, the model opens up a powerful avenue for evaluating “what-if" scenarios under a variety of social, ecological, and policy conditions, providing critical insights for researchers and decision-makers interested in fostering transformative change towards more resilient agricultural and food systems.

This first discussion section outlines the central elements and processes of the InSEEDS model structure, situates them within the empirical literature, and illustrates how these findings can be interpreted more broadly for the field of World-Earth modelling. Simulations point to the manifold ways in which social networks, and the way they structure interactions between farmers matter in the adoption of agricultural practices. This comprises both social norm effects, as well as social learning within the farmer networks. The importance of local connections and information for the adoption of novel agricultural practices has been investigated extensively in the literature (Wenger, 2011; Casagrande et al., 2016; Hes and Rose, 2019). Information obtained from neighbouring farms, over-the-fence-exchange (Casagrande et al., 2016), and local social norms (Burton et al., 2020; Swart et al., 2023) have been highlighted as key processes in farmer decision-making globally. Studies from Vietnam emphasize the importance of descriptive social norms (Tran-Nam and Tiet, 2022). Kuhfuss et al. (2016) stress the importance of information on other farmers' pro-environmental practices as a key factor for farmers retaining pro-environmental practices after implementing them in France. Westerink et al. (2021) point to the importance of shifting cultural norms related to the concept/image of a "good farmer" (Burton et al., 2020) towards nature-inclusive farming for the adoption of pro-environmental farming practices in the Netherlands. Villamayor-Tomas et al. (2019) investigate non-monetary incentives for adoption of environmental farming practices and point to the importance of other farmers' behaviour (i.e., descriptive social norms) for farmer participation in agro-environmental programs in Spain, Germany and Switzerland. Nykvist (2014) points to the fact that for Swedish farmers, different social learning processes matter, and that "learning among farmers is inherently social" (p.436). However, the study also emphasizes that in order for social learning to support sustainable natural resource management, it has to be accompanied by adequate policy, leadership, and other facilitating (infra)structure. Social influence can thereafter be regarded as an important entry point to understanding farmer decision-making, but shall not be seen as a silver bullet solution. To further support a more widespread adoption of RA, other active levers like policy, economics, or extensionist services should be considered additionally.

The use of network approaches in ABMs has been a standard for years (Kim, 2009; Alam and Geller, 2012). In InSEEDS v0.2, we use one simple network topology – a lattice graph capturing each agent's cell's Moore Neighborhood – for two distinct processes and already find the interaction of these different information sources within decision-making to be of central importance for simulation results.

Asides from the model mechanisms resting on local social networks and social influence, social-ecological learning was found to be decisive for attitude formation, and had an even larger impact than social learning on simulation results. In InSEEDS, we therefore expanded our understanding of learning from a purely social to a social-ecological process, and used this in the conceptualisation of a dynamic attitude component. Evaluating one's own land, thereby learning from it, and potentially adapting one's management strategy accordingly, can be regarded as a common single-loop learning process in farming (Pahl-Wostl, 2009; Marquardt Arévalo et al., 2010). The shift from understanding learning as a *social*, to a more broadly *relational* – including both social and social-ecological interactions– process (Janssen et al., in prep) expands the possibility space of understanding the manifold ways in which learning processes shape human behaviour (Satake et al., 2007; West et al., 2020; Walsh et al., 2021; West et al., 2024). Especially in the context of RA, the importance of radical, transformational relational learning processes has been shown in literature (Gosnell, 2022).

Heterogeneity, ecological and social, play a central role in adoption dynamics. While emphasising on heterogeneity, especially in agent decision-making, has long been called for in often regionally focused agent-based models (Schlüter et al., 2012; Halbe et al., 2015), it becomes even more imperative considering broader spatial scales (Malek et al., 2019; Malek and Verburg, 2020). This is not only applicable to the social dimension of WEMs, but includes a heterogeneous representation of ecological

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conditions as well. The simple distinction of two AFTs in InSEEDS v0.2 already points us to the importance of representing both social and ecological heterogeneity; the AFT share is decisive for spreading dynamics –with a difference of RA adoption rates of up to 50% in scenarios varying this parameter–, and regionally different ecological conditions impact the evaluation of success of agricultural management strategies. Especially in the field of WEM, agent diversification should therefore be prioritised. The diversity of human decision-making in general is a widely-accepted fact in psychological research; its impact on simulation modelling results has recently gained interest in the WEM community (Moore et al., 2022). The distinct and context-dependent transition pathways different farmers and farms exhibit in their switch to more sustainable, or RA practices is also an established scientific fact (Casagrande et al., 2016; Malek et al., 2019).

This second subsection interprets and discusses the simulation results with an emphasis on the ecological outcome parameters. Our modelling results point to the overall positive ecological performance of CT as an RA practice globally, confirming previous LPJmL work on the subject (Herzfeld et al., 2021). The parameter sensitivity results show that, if decision-making were solely centred on ecological performance (i.e., the attitude-based model component), we observe a higher adoption of RA globally in model simulations. However, descriptive social norms representing CF as a widely-spread and often dominant practice hamper the spreading of the on average ecologically-superior CT practices. The positive impact that CT, as an RA practice, exerts on SOC levels will likely play an increasingly central role in the future of farming under climate change pressures (Rockström et al., 2009, 2014). Soil water holding capacity has been show to significantly increase under CT, which is essential for coping with dry spells and other extreme events (Bescansa et al., 2006). Regarding the reflection of possible ecological impacts of agricultural transitions towards RA, we acknowledge that the current representation building solely on CT reflects a limited view on RA, especially regarding the more context-specific tailoring of different RA practices. With our current representation of RA, we thereafter likely draw an "underperforming" image of the ecological outcomes RA could have globally. While our indicators SOC and CY don't show drastic increases in the order of magnitude that outcomes differ between the lowest and highest RA adoption rates (2% for both over the course of the simulation period of 78 years), from a global perspective, such differences are still decisive. The "4 per 1000" initiative, is an illustrative example: it was launched just before the COP-15 conference and advocates for an annual 0.4% increase of SOC to be a leeway to foster food security and climate resilience (Rumpel et al., 2018).

Still, it is important to note that while we use CT as a representative RA practice, many definitions of RA, especially in practitioner-dominated contexts, are outcome-, rather than practice-driven (Newton et al., 2020; O'Donoghue et al., 2022; Jayasinghe et al., 2023; EARA, 2024; Berthon et al., 2025). We selected CT as our initial representative RA practice because it is considered one of the most broadly applicable individual management options, with demonstrated positive effects on ecological indicators. While, given the current modelling setup, we have to provide farmers with a range of practices to chose from, the way we implement the farmer decision-making function is clearly outcome-oriented. This means that if farmers were to observe that on their own land, under CT, SOC and CY decline, and that their neighbours practising CF reach better ecological performance, CF would be their (attitude-based) adoption choice, which is based on an outcome-oriented evaluation.

A balanced consideration of both SOC and CY is the most desirable approach to increase both ecological indicators in conjunction, as CY drops to rather low levels when farmers only consider SOC in their decision-making. The difference is

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less pronounced, but also there, in the resulting SOC levels when farmers only consider CY in their decision-making. The small overall impact of the variation of these parameters also points to certain synergy effects: Globally, on average, choosing CT instead of CF leads to an increase in SOC. The combination of an increase in SOC, as well as better soil water retention through the residues left on the field, in most cases, entails a significant increase in CY (Lal, 2020; Herzfeld et al., 2021). This balanced consideration is important especially when considering agricultural systems that are socially and ecologically resilient to future farming conditions under climate change pressures. While emphasizing on high levels of SOC only is presumably very supportive of strengthening the soil carbon sink and fostering soil biodiversity, stable, agricultural agricultural productivity in terms of CY also has to be sustained for a resilient and regenerative agricultural system.

6 Limitations and Future Directions

As an innovative approach to simulating co-evolutionary dynamics in World-Earth and Human-Land Systems, InSEEDS makes important advances in our ability to investigate land-use transitions across scales. However, InSEEDS has several limitations, both the representation of social and and social-ecological dynamics in the ABM subcomponent, as well as the representation of RA in LPJmL. In this section, we systematically discuss key limitations of InSEEDS and outline concrete pathways for addressing these challenges.

One methodological limitation is the need for large computational resources and high-performance computing (HPC) to run InSEEDS simulations due to the computational requirements of the LPJmL model component. This entails a limited model accessibility, and the feasibility of computationally intensive analyses, such as large ensembles or Monte Carlo simulations.

The current ABM component in InSEEDS adopts a representation of farmer decision-making that explicit economic (e.g., markets, farmer income, consumer demand) and political factors (e.g., policy incentives, governance structures). InSEEDS is designed to allow seamless integration of multiple agent-based modelling elements to represent different types of agents (e.g., farmers, consumers, or governments) and their processes within and between taxa. The number and complexity of such processes depend on the degree of coupling between taxa, especially with ENV (LPJmL). In the ABM component, we plan two main future model development strands: the refinement of the individual farmer decision-making representation, as well as the addition of different processes at a higher level of social organisation. On the individual level, this includes the representation of different learning processes and more decision-making heterogeneity. Towards HLSO, non-local farmer networks, and more macro-level variables and influences, like governance and market structure, legislative bodies, and macroeconomic factors, as well as novel AFTs beyond the role "farmer", shall be added subsequently.

A further key limitation of the current InSEEDS model version is its relatively homogeneous representation of farmer decision-making. Considering the farmer AFTs distinguished in the present implementation, the social diversity of agents and the range of behavioural responses to ecological or social cues remain limited. Although even small differences in AFT parametrization have illustrated the substantial influence that heterogeneity exerts on model outcomes, especially at broader spatial scales, representing only two types is ultimately insufficient for capturing the broad spectrum of farmer strategies, risk

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perceptions, and adaptation pathways encountered in real-world agricultural systems. Especially in the simulation of up-to-global dynamics, this lack of agent diversity becomes an increasingly central limitation.

The importance of considering social and ecological heterogeneity in an intertwined fashion becomes evident in examples like the country-scale Paraguayan simulation dynamics. Here, ecological heterogeneity is resolved via the LPJmL-based environmental model component. Ecologically, the legacy effects of a more recent conversion of natural vegetation to cropland, for example, as compared to Europe becomes evident: SOC levels and CY generally decline over the simulation period.

The decision-making model, however, is less spatially differentiated and uses simplified logic: agents compare current ecological performance to a previous benchmark (either the start of the simulation or the time of their last strategy switch). Under scenarios where ongoing declines in SOC and CY are observed, this approach systematically feeds dissatisfaction, triggering frequent practice switches and, as seen in northwestern Paraguay, large-scale adoption of CF, at odds with historical trends (Paraguay is considered a "CT success story" and, through a steady switch away from CF over the past decades, has reached an adoption of CT practices that reaches up to 100% (Kassam et al., 2019)). Thus, we can say that the simulated decision-making model dynamics do not represent a likely future behaviour. Here, the importance of a spatially-explicit, diversified decision-making model becomes evident. While the comparison mechanism implemented might work well to evaluate European ecological performance with regard to soil dynamics, given their more realistic representation in the LPJmL model component, it does not do justice to South American Lands with a much more "young" agricultural land use. Looking ahead, addressing this limitation will require diversifying both the agent pool (through additional AFTs calibrated to empirical data and regional behavioural diversity) and the comparison mechanisms used in decision-making (for example, by considering rates of change under distinct management regimes, rather than absolute differences, as the benchmark for satisfaction or dissatisfaction). This diversification aligns with broader calls in the literature to more fully represent the spectrum of social-ecological feedbacks and behavioural drivers in World-Earth system models (Beckage et al., 2022).

While a primarily theory-based approach, as followed in InSEEDS, can offer an alternative to a purely empirically-driven model building procedure (Arneth et al., 2014), this entails central shortcomings with regard to model applications that aim for a high degree of realism. Future applications of this kind can work on the inclusion of different sources of qualitative and quantitative data. For example, decision-making typologies (e.g., Malek and Verburg (2020)) can help structure more diverse conceptualisations of human decision-making, while results from global surveys like the world values survey can support the socio-culturally sensitive parametrisation (Haerpfer et al., 2022).

Furthermore, the farmer network currently only involves the local, geographically-bound connections provided by the LPJmL grid. However, it is evident that non-local connections and social networks based on other forms of proximity also play a role for farmers. Future refinements could include multi-layer networks using different topologies (Boccaletti et al., 2014). Representing the multi-fold importance of networks can be understood as a central frontier in AB-DGVMs.

InSEEDS only includes stochasticity in the process of allocating the different AFTs to the LPJmL grid cells during the InSEEDS model setup, while and not during model simulations. The use of stochasticity for AFT-cell allocations results in AFT-distinct social-ecological interactions at cell level. This different bi-directional interaction of the ABM with the LPJmL component gives rise to non-deterministic model behaviour across model simulation runs. As our intention with this first ver-

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sion of the novel and highly complex InSEEDS model was the set-up of a model system that favours transparency and traceability, we decided against the inclusion of stochasticity within model simulations, i.e., in the representation of the decision-making process. This way, we were able to focus on better understanding the internal co-evolutionary model dynamics and interactions. Once the foundation is well-understood, and with model purposes that strive towards more realism, stochasticity can be introduced incrementally to address variability and uncertainty.

Development perspectives for the environmental InSEEDS component are centered on the biophysical representation of RA, which is currently subject to a simplified, practice-based approach. For this model version, we chose CT as one of the few RA practices that is widely applicable in crop-based agricultural systems across different climate zones and biophysical conditions (Wang et al., 2006; Liang et al., 2025). This model version lacks the representation of further agricultural management options, e.g., water management, intercropping, green or brown manure, and multifunctional land-use options like agroforestry and the inclusion of (grazing) animals into farming systems (Schreefel et al., 2020). As the application of many RA practices is highly context-dependent (EARA, 2025), the application of those practices beyond CT should be adjusted to contexts in large-scale simulations. Basing our evaluation solely on CT, our already positive results reflected in the ecological indicators likely underestimate the potentially positive effects that a more broad, context-adapted implementation of RA practices can have. The inclusion of additional biophysical indicators, like soil water holding capacity, in our simulations represents another important development direction to capture water as a central bottleneck in agriculture, especially under exacerbating climate change impacts. Furthermore, a more outcome- than practice-based definition of RA is an interesting research direction to explore further (Newton et al., 2020; Sands et al., 2023). While an outcome-based evaluation is already reflected in the attitude component of the decision-making process, this dimension could be emphasised further in our overall RA definition approach, that currently rests on management practices within LPJmL.

Developments in the socio-cultural and environmental components also facilitate the diversification of social-ecological interactions in the socio-metabolic (MET) taxon of the model. Future expansions in this field could be the broadening of the farmer agricultural management and land-use practices that can be put into place (social –> ecological). Moreover, the set of biophysical information that can be used by the ABM agents (ecological –> social) could be expanded: While farmers currently only use information on SOC and CY, other parameters, like soil moisture, might also be relevant to consider. LPJmL offers a whole range of different model input (>45) and output (>300) variables that can form the basis for a wide variety of social-ecological processes and interfaces. For example, land use or water use and irrigation can be coupled as inputs for LPJmL, enabling land-use or socio-hydrological modelling with the underlying processes (Rounsevell et al., 2014; Kreibich et al., 2025). Corresponding ENV feedbacks could be, for example, harvest or river discharge, coupled as LPJmL outputs, which in turn could be used in new processes such as harvesting. New types of biophysical information, such as water level measurements, or the Planetary Boundary, status might be useful to consider for novel actors at higher levels of social organisation (e.g., governmental or market actors).

The aforementioned limitations currently lead to model version with limited / expandable model realism. However, it is important to note that a *full* or *entirely realistic* representation is not the goal of the InSEEDS model in general, and especially not for this first model version. Here, we aim to provide a first, one-of a kind, up-to global scale, World-Earth model of land-use

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change. Rather than serving as a "digital twin" of reality, this tool is intended to dynamically explore future scenarios of land system changes at up to planetary scale.

7 Conclusions

This study introduces the InSEEDS World-Earth model as an important methodological advancement in co-evolutionary modelling of land-use transitions, spanning from local landscapes to the planetary scale. By integrating a process-based Dynamic Global Vegetation Model (LPJmL) with an agent-based model of socio-cultural dynamics, InSEEDS provides a novel tool for investigating how feedbacks between ecological systems, farmer decision-making, and social interactions shape the adoption and outcomes of RA practices. The model successfully captures the influence of both social and ecological heterogeneity in decision-making processes, emphasizing the significance of social norms, different learning mechanisms, and environmental feedbacks. However, certain limitations remain, including the simplified representation of agent decision-making processes, the lack of influences such as economics and politics, and the need for broader agent heterogeneity. Future research should expand on these aspects by incorporating additional farmer types, higher levels of social organisation, and empirical validation. Enhancing the model's resolution and realism will be crucial for refining our understanding of large-scale land-use transformations and informing policy strategies for a more resilient and regenerative agriculture.

Our analyses demonstrate that both ecological and social heterogeneity—embodied here in diverse biophysical conditions, heterogeneous agent types, and explicit modelling of social norms and learning—are essential for representing the complex pathways and barriers to large-scale adoption of regenerative agricultural management. The model's results underscore the importance of social networks, decision-making inertia, and the local context in the emergence of agricultural transitions.

While InSEEDS necessarily adopts simplifications in, for example, the diversity of AFTs, the range of management practices, and the representation of economic and policy drivers, this modular, extensible framework is explicitly designed to enable future refinement. We have outlined clear development pathways, such as the inclusion of additional empirical data, more nuanced social and biophysical processes, networks of greater topological complexity, and a broader array of regenerative practices.

Ultimately, this first version of InSEEDS serves both as a proof of concept and as an invitation to the research community. Expanding the model's realism and empirical grounding is the key to addressing outstanding questions about tipping points, resilience, and transformation in land systems. The InSEEDS framework offers a flexible foundation to co-develop new capabilities and explore "what-if" scenarios for large-scale agricultural and land system change.

By fostering interdisciplinary integration and providing an open platform for future collaboration, InSEEDS aims to advance both fundamental understanding and actionable insights for regenerative and resilient food systems worldwide.

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Code and data availability. The code used to generate the results presented in this study is available on GitHub at https://doi.org/10.5281/zenodo.14265856. The repository includes the Python code for the InSEEDS model, as well as the scripts used to run the simulations. The copan:LPJmL modeling framework that was used to build the InSEEDS model can be found on GitHub at https://doi.org/10.5281/zenodo.14246191. The data used to set up LPJmL spin-up simulations can be found at https://doi.org/10.48364/ISIMIP.982724.2 (Lange et al., 2023). The data used to determine the initial distribution of management practices during the InSEEDS model initialisation can be found at https://doi.org/10.5194/essd-11-823-2019 (Porwollik et al., 2019)

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