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Towards sustainable agriculture: behaviors, spatial dynamics and policy in an evolutionary agent-based model

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Towards sustainable agriculture: behaviors, spatial dynamics and policy in an evolutionary agent-based model

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Abstract

Economic and population growth increasingly pressure the Earth system. Fertile soils are essential to ensure global food security, requiring high-yielding agro-technological regimes to cope with rising soil degradation and macro-nutrients deficiencies, which may be further exacerbated by climate change. In this work, we extend the AgriLOVE land-use agent-based model (Coronese et al., 2023) to investigate trade-offs in the transition between conventional and sustainable farming regimes in a smallholder economy exposed to explicit environmental boundaries. We investigate the ability of the system to favor a sustainable transition when prolonged conventional farming leads to soil depletion. First, we showcase the emergence of three endogenous scenarios of transition and lock-in. Then, we analyze transition dynamics under several behavioral, environmental and policy scenarios. Our results highlights a strong path-dependence of the agricultural sector, with scarce capacity to foster successful transitions to a sustainable regime in absence of external interventions. The role of behavioral changes is limited and we find evidence of negative tipping points induced by mismanagement of grassland and forests. These findings call for policies strongly supporting sustainable agriculture. We test regulatory measures aimed at protecting common environmental goods and public incentives to encourage the search for novel production techniques targeted at closing the sustainable-conventional yield gap. We find that their effectiveness is highly time-dependent, with rapidly closing windows of opportunity.

Keywords: Agriculture, Land use, Agent-based model, Technological change, Transition, Environmental boundaries, Sustainability

JEL codes: C63, Q10, Q15, Q16, Q18, Q50, Q55

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1 Introduction

With the global population projected to increase steadily during the next century and soil degradation already affecting worldwide the cultivation of major crops, agricultural systems are in need of finding sustainable intensification strategies quickly (Rockström et al., 2017; Ramankutty et al., 2018; Tilman et al., 2002). This is even more evident in the case of smallholder farming systems, where structural vulnerabilities acerbate the effects of shocks. Drawing upon the *Limits to Growth* literature on transitions (Meadows et al., 1972; Meadows and Randers, 2012), and building on the literature on planetary boundaries (Rockström et al., 2009; Steffen et al., 2015b), evolutionary theories of technical change (Nelson and Winter, 1982; Dosi et al., 1988, 1995; Dosi and Nelson, 2010) and energy transitions (Lamperti et al., 2018), this paper studies transition dynamics between agro-technological regimes under soil degradation. A *conventional* farming regime, higher yielding in the short term but extractive of soil resources, is juxtaposed to a *sustainable* regime, lower yielding in the short term but balanced in soil usage. Utilizing a spatial land-use agent-based model (ABM) called AgriLOVE (Coronese et al., 2023), we explore how behavioral, social and environmental factors influence the diffusion of sustainable farming and how transition dynamics reflect on food production and its relative scarcity, given an exogenously growing demand.

In the past 40 years, almost one third of the world's cropland has been abandoned because of soil erosion and degradation (Pimentel and Giampietro, 1994). Loss in soil organic matter by intense cultivation is often hypothesized to be a major cause of the continuing clearing of forest for agricultural land (Nye and Greenland, 1965; Andriesse, 1977; Bauters et al., 2021), with agriculture accounting for 80% of deforestation activities (Kendall and Pimentel, 1994). Increasing environmental pressure on soils is unlikely to revert soon, as the world population continues to grow faster than food supply in the Global South, and economic well-being shifts diets towards animal products (Delgado et al., 2001). In this context, adopting sustainable intensification techniques is a pressing concern for smallholder farming systems (Ramankutty et al., 2018) and the identification of rapid conditions for such a transition becomes vital (Tilman et al., 2002; Foley et al., 2011). Focusing on soil depletion and its consequences, this study investigates agro-technological transitions in presence of loss of soil productivity driven by men-induced soil degradation.

Two alternative production regimes stylize the nature of current systems of food production: conventional and sustainable farming. Conventional farming has enabled agriculture to meet the growing demand during the past decades (Ramankutty et al., 2018), but has extensively damaged soil health and soil resource endowment (Van Diepeningen et al., 2006). Sustainable farming is a greener alternative, less impacting and with fewer negative externalities thanks to the reintegration of soil macro nutrients. However, it is frequently less yielding, at least in the short term (Rockström et al., 2017). These two regimes represent two different schemes of incentives for smallholder farmers (Tilman et al., 2002): intensification versus preservation of ecosystem services.[1] Trade-offs between these two incentives have recently become prominent, as shocks to the smallholder farming

[1] Society receives from natural and managed ecosystems numerous ecosystem services (Tilman et al., 2002; Daily, 2013). Among others, forest and grassland ecosystems, which can create or regenerate fertile soils (Tilman et al., 2002).

systems have become more frequent (Yiridoe et al., 2005).

The quest for a rapid sustainable intensification calls for identifying dynamics, individual and collective interventions, which could allow a reversion of the current (unsustainable and inequitable) trends in food production systems (Steffen et al., 2015a; Chapin III et al., 2010). This entails identifying tipping points in food system transitions, which can either disrupt the system (i.e., negative tipping points) or trigger increase societal resilience (i.e., positive tipping points). In this perspective, non-linear complex approaches like agent-based models offer a unique opportunity for behavioral characterization while studying socio-ecological transitions.

Focusing on scenario analysis, the agent-based model AgriLOVE provides a laboratory for modeling trade-offs between the increasing need for agricultural output and the constraints imposed by eroding soils (Coronese et al., 2023). AgriLOVE is populated by spatially-located, heterogeneous, boundedly-rational agents competing on markets and searching for innovations to satisfy a growing demand for food while coping with finite resources, alternative land-management practices, and climate-related shocks (Coronese et al., 2019) that might adversely affect agricultural productivity (Palagi et al., 2022). Agents adaptively react to the perceived state of the system, dynamically adjusting production, inputs, production techniques and land usage (e.g. by abandoning unprofitable crops or deforesting virgin areas). The model is well-suited to generate insights on how economical, social and environmental factors influence the agents' decision of adopting a given farming regimes. In this study, looking at the agricultural sector as a socio-technical system (Li et al., 2015), we investigate patterns of transition to sustainable solutions and highlight what factors can stimulate or retard the transitions.

The paper largely draws on the insights offered by the evolutionary theory of agricultural modelling (Janssen and Ostrom, 2006; Berger, 2001; Berger and Troost, 2014) and of technological change (Dosi, 1988; Silverberg et al., 1988; Silverberg, 1991; Nelson and Winter, 1982; Fagiolo and Dosi, 2003; Dosi et al., 2010), building especially on the analysis of farmers' behaviors, learning ability and proximity-related effects (Berger, 2001; Niamir et al., 2018). We contribute to this literature by using AgriLOVE as a simulation laboratory to investigate transition scenarios in presence of soil degradation. While existing studies on farming system transitions focus on specific regions and climatic conditions both in the Global North and Global South (Nieddu et al., 2021; Marvuglia et al., 2022; Gebrehiwot et al., 2022), we offer a system-wise approach to model transitions and their implications. We compare endogenously emerging regimes of agricultural production and their stability to alternative institutional, environmental and behavioral settings in the short and in the long run. Modelling how distinct conventional and a sustainable paradigms interplay in presence of technical change, we study trade-offs in terms of natural resources protection (i.e. deforestation and soil degradation), food security and spatial segregation providing scenarios for each condition. To the best of authors' knowledge, such analysis on sustainable transitions is currently missing in the literature.

Our simulation results first demonstrate the model's capacity to endogenously generate diverse transition scenarios: an "early transition" where sustainable farming is adopted promptly alongside environmental depletion, a "late transition" characterized by overshooting dynamics and subsequent system recovery, and a "conventional lock-in" scenario dominated by conventional farming. We subsequently examine a range of behavioral, environmental, and institutional factors to investigate their impact on impeding or promoting sustainable transitions. Interestingly, we find a mild indication that too much information about neighbors' performance can hurt; indeed, limited processing of information appears to partially counterbalance the tendency of agents to switch towards short-run gain-yielding agricultural techniques. Beyond this effect, our results suggest that behavioral adjustments are not sufficient to consistently support the diffusion of sustainable agro-technological regimes. This highlights the need for policy interventions. Negative tipping points are instead visible in scenarios involving rapid and delayed soil degradation. Our findings reveal that the likelihood of a sustainable transition is negatively impacted by the speed and timing of soil erosion exceeding certain thresholds. This indicates a limited capacity of the system to cope with swift and abrupt environmental deterioration, primarily due to inefficient and slow decentralized coordination among agents. Additionally, we highlight the existence of non-trivial spatial dynamics and underscore the pivotal role of forest preservation in promoting sustainable transitions. We demonstrate that the exploitation of virgin lands by incumbent farmers grants a competitive advantage that, through path-dependency, reduces the likelihood of effective sustainable farming diffusion. Our policy experiments reveal a substantial space for policy intervention, with both regulation of forest exploitation and subsidies incentivizing the search for novel production techniques leading to a significant increase in transition likelihood. Importantly, our results indicate a strict window of opportunity for policy deployment, with delayed interventions being inconsequential due to the path-dependency in technical adoption dynamics.

The paper is structured as follows: Section 2 contextualizes the paper within existing debates, while Section 3 provides an extensive description of the regimes of conventional and sustainable agriculture. In Section 4, we offer a concise description of the AgriLOVE model, along with a detailed exposition of the novelties introduced in this work. Results are presented in Section 5. Section 6 discusses policy implications. Finally, Section 7 concludes the paper and offers a discussion on the future developments that we envision.

2 Related literature

Transitions, led by technological advances, can be seen as evolutionary processes (Foxon, 2011). In the literature on energy system and industrial dynamics, studies about the dynamics of transition to sustainable production are prevalent (Lamperti et al., 2020, 2018; Markard et al., 2012; Dosi and Nelson, 2010). As farming systems are increasingly understood as complex socio-technical adaptive systems (Darnhofer et al., 2010), the body of work on sustainable transitions among agro-technological regimes is also growing (Markard et al., 2012).

Sustainable transitions involve the development and diffusion of alternative agro-technological regimes characterized by a reduced negative (or even neutral) impact on the natural environment. The simulation of scenarios through numerical models accounting for innovations (to be read as changes in production techniques) and their diffusion is a natural tool to uncover transition dynamics and capture bottom-up effects unfolding over potentially long horizons (Kemp, 1994; Balint et al., 2017a; Dosi and Roventini, 2019). This is particularly relevant for smallholder farming settings, where the lack of sufficiently detailed data makes experimental and empirical assessments particularly difficult (see Jones et al. 2017). Agricultural economic simulation models have indeed explored the dynamics of sustainable transitions. A first example can be found in Dabbert and Madden (1986), who developed a multi-year simulation model to analyze the transition toward organic agriculture. In land-use models, such as those presented by Valente and Rogers (1995); Parker et al. (2003); Berger et al. (2006), transitions are often significantly influenced by peer learning dynamics.

Agent-based models are particularly well-suited for characterizing the nonlinear dynamics inherent in socio-ecological transitions (Bonabeau, 2002; Farmer and Foley, 2009; Dosi and Roventini, 2019). ABMs have proven successful in modeling agricultural systems across various geographical setups (see Schreinemachers and Berger 2011, Berger and Troost 2014, Bousquet and Le Page 2004, Matthews et al. 2007, Kaye-Blake et al. 2010 for literature reviews on this topic) and to new farming practices diffusion (e.g. Berger, 2001; Bert et al., 2011). However, ABMs focusing on transitions toward more sustainable agro-technological regimes are still limited and often confined to specific geographical areas. The agent-based model developed by Deffuant et al. (2002), based on an earlier version by Chattoe and Gilbert (1998), examines the innovation diffusion of an organic farming paradigm in the French *département* of Allier. Similarly, Kaufmann et al. (2009) presents an ABM on the diffusion of organic farming practices in Latvia and Estonia. Both models highlight the critical role of social interactions in facilitating conversion, but they also emphasize that economic and environmental factors significantly impact transition likelihood. In an effort primarily focused on assessing the effects of agents' interactions, Marvuglia et al. (2022) combines ABM with large-scale environmental Life Cycle Assessment and naive Bayesian modeling to illustrate the evolution of green consciousness among farmers in Luxembourg. Exploring aggregation forces, Olabisi et al. (2015) investigates how individual decision-making processes aggregate at the landscape level to influence sustainable transitions in the Philippines.

We aim to contribute to this debate by proposing a complementary analysis compared to existing geographically-explicit models. Our approach involves expanding a recently developed land-use agent-based model, AgriLOVE (Coronese et al., 2023). AgriLOVE explores land use and technological change in an agricultural sector subject to environmental boundaries, finite available resources, and changing land productivity. Drawing on the extensive tradition of existing agriculture and land-use models (e.g. Parker et al., 2003; Happe et al., 2006; Barnaud et al., 2007; Bert et al., 2011; Berger et al., 2006), AgriLOVE complements existing frameworks by investigating bottom-up macro-level dynamics and their unfolding over long-run horizons. In this evolutionary model environment, where agents do not optimize utility or profit functions, neither dynamically nor myopically (Coronese et al., 2023), agents' dynamics are influenced by both spatial proximity (as in Thebaud et al., 2001) and social proximity (as in Janssen, 2007; Courdier et al., 2002). Technical change is modeled endogenously, with the process of innovation and the diffusion of production techniques serving as key drivers of farm productivity. This feature makes the model suitable for studying the emergence of novel (stable or unstable) regimes of sustainable agricultural production resulting from farmers' interactions with the environment in markets and space (Coronese et al., 2023).

In examining sustainable transitions through AgriLOVE, we extend farmers' decision processes to encompass dynamics generated by the interaction between the food market and the establishment of a new sustainable agricultural regime, all while considering explicit environmental boundaries. Departing from geographically-focused studies, we opt for a spatially explicit model that mirrors smallholder agricultural economies. This approach accommodates transition solutions at a macro scale and incorporates spatial mechanisms of path dependence in transitions (Martin and Sunley, 2006). This feature facilitates a more comprehensive understanding of the future of alternative regimes in such economies, providing a simulation laboratory to qualitatively explore the emergence of sustainable patterns of food production. This insightful economic modeling exercise (as defined by Nelson (2016)) is particularly relevant in smallholder farming settings. In these contexts, where regional data is often insufficient to explore how transitions and trade-offs develop, it becomes challenging to conceive policies capable of supporting and enhancing the sustainable intensification of the food system without the aid of a modeling approach.

Finally, exploring trade-offs in the food system, agriLOVE may act as a laboratory to identify negative (Steffen et al., 2015b; Loorbach et al., 2016; Lenton et al., 2008) and positive (Tàbara et al., 2018; Lenton et al., 2023) sensitive intervention points for sustainable transitions in the agricultural sector (Farmer et al., 2019). While in this work we find only limited evidence supporting the existence of positive tipping points, contrasting with the abundance of negative ones, AgriLOVE can be further expanded to identify positive tipping points and explore virtuous behaviors that can unlock transformative solutions. Moreover, the paper directly aligns with the climate/environmental Agent-Based Modeling (ABM) literature (Balint et al., 2017b; Lamperti et al., 2019), complementing a strand that has recently delved into the issue of transitions to green energy and green capital (Lamperti et al., 2020; Hötte, 2019; Nieddu et al., 2021).

3 Agricultural regimes: conventional *versus* sustainable

Existing agro-technological regimes can be categorized according to their impacts on ecosystems (Pretty, 2018). Broadly, the literature distinguishes between *conventional* and *sustainable* agricultural regimes (Saifi and Drake, 2008; Ramankutty et al., 2018; de la Cruz et al., 2023; Kamau et al., 2023):

- *Conventional* farming is a system where synthetic pesticides, herbicides, and fertilizers are typically used to maximize crops' yields. The definition is adopted by the International Federation of Organic Agricultural Movements (IFOAM) to define farming production, or regime that is not sustainable or in "conversion" (IFOAM, 2012). Conventional farming requires a significant amount of chemical and energy input and may weaken the ecology of a landscape (Schrama et al., 2018). For example, relying on the intensive application of mineral fertilizers has contributed to the loss of soil organic carbon, environmental pollution, loss of biodiversity, and adverse climate change (de la Cruz et al., 2023; Allam et al., 2022; Martini et al., 2004). It follows that in conventional farming higher yields in the short-run are attained along with larger environmental costs (Wu and Sardo, 2010; de la Cruz et al., 2023), possibly leading to stagnating or even descending trajectories of soil productivity. Such patterns have already been observed in several areas of the globe (Ray et al., 2012). Conventional farming is frequently paired with mono-cropping: such uniformity boost yields by reducing labor and capital costs, and by making harvesting easier. However, this practice further reduces agrobiodiversity and increases crops susceptibility to pathogens (Gabriel et al., 2013). Overall, in conventionally farmed systems, biodiversity, soil fertility, and ecosystems health are usually compromised (Huntley et al., 2013; FAO., 2013).

- *Sustainable* farming (or organic farming) is a broad term, identifying all those farming systems that emphasizes the use of green management practices, such the reintegration soil nutrients during the production process (Commission and Organization, 2007; Shennan et al., 2017). It relies on ecological processes, biodiversity and cycles adapted to local conditions, rather than the intensive use of chemical inputs (Gomiero et al., 2011; Shennan et al., 2017). Promoting ecosystem health, sustainable farming regimes reduce the clearing of primary ecosystem (e.g., forest) (Scialabba and Müller-Lindenlauf, 2010) and reduce the use of inputs while increasing carbon sequestration (Smith et al., 2019), triggering positive externalities for the environment as a whole (Rockström et al., 2017). If environmental benefits of sustainable farming regimes are unequivocally recognized (Robertson et al. (2014), for a review see de la Cruz et al. (2023)), yield performances are usually lagging behind with respect to those of conventional systems (Pant and Hambly-Odame, 2009; Ponisio et al., 2015; McKenzie and Williams, 2015; de la Cruz et al., 2023; Smith et al., 2019). Examples of sustainable farming techniques are integrated pest management, agroforestry, conservation agriculture and irrigation water management (Pretty, 2018).

Therefore, conventional and sustainable regimes present a key trade-off between short and long-run levels of yields. In the short term, higher yields reward conventional farmers: this will consequently boost farm productivity and mitigate food insecurity in the short-run, but at the cost of natural resources depletion in the long term (Tilman et al., 2001), since soil nutrients and organic carbon are not reintegrated (Mazzoncini et al., 2010). Conversely, sustainable farmers will experience lower yield in the short run, but they are less likely to suffer from some types of soil degradation in the long-run. The existence of productivity gaps among the two regimes is highly documented (Ponisio et al., 2015; de la Cruz et al., 2023) and evidences are now emerging on the catching-up potential of sustainable farming (de la Cruz et al., 2023). If without environmental stressors, conventional farmers can produce between 15% and 30% more than sustainable farmers (Gabriel et al., 2013), in conditions of stress (such as under soil deterioration) sustainable farming is able to usually guarantee a better yield (Gomiero et al., 2011; Kamau et al., 2023). This is determined by the intrinsic correlation of the soil organic carbon and crop yield, which results in a competitive advantage for those sustainable systems able to reintegrate nutrients (especially nitrogen, phosphorus and potassium) in terrains (Biswas and Benbi, 1996; Ferng, 2005; LI et al., 2018; de la Cruz et al., 2023). In Section 4.2 we describe how these two alternative agricultural regimes are formalized in the model.

4 The model

We employ AgriLOVE, a spatially explicit agriculture and land-use ABM model (Coronese et al., 2023). The model targets a smallholder farming system and can be effectively used to investigate diffusion patterns of different agricultural technical paradigms under several scenarios. The focus on smallholder farming is justified under two lenses: firstly, the smallholder farming system is the predominant farm holding globally; secondly, macro-level dynamics emerging from technological innovation and diffusion choices by smallholding agents are usually modeled utilizing location-specific narratives (see the family of MP-MAS models Berger, 2001; Berger and Troost, 2012, 2014). AgriLOVE model proposes a complementary tool to these models, where emerging macro-level patterns can be analyzed through a spatially explicit grid - at the present stage not calibrated on location-specific data.

Section 4.1 contains a short recap of the main characteristics of the model , while Section 4.2 discuss the main novelties on technological alternatives introduced in this work. Appendix B contains the additional equations governing the described mechanisms. See Coronese et al. (2023) for further details on the model.

4.1 The model in a nutshell

Physical space is explicitly represented through a 2-dimensional cell grid, with each cell symbolizing an idealized plot of land (Jones et al., 2017). Each cell i can be either a cultivated area, an abandoned one, or covered with forestry (virgin areas). At each time step t, a farm operates on each cultivated cell. The model is populated by N_t firms (indexed by z), with the possibility of owning more than one farm (Moser, 2020). Each farm is endowed with an initial productivity θ_{i0}, reflecting the heterogeneous pre-determined pedo-climatic characteristics of the land on which they carry out production (Fatichi et al., 2020). Farms combine labor and land to produce a homogeneous bundle of food (a representative crop ideally composed of cereals such as maize, wheat, soybean, and rice, Grassini et al., 2013). The amount of food produced depends on farm productivity and exhibits decreasing marginal returns from labor (see Equation B.1).[2]

4.1.1 Farm productivity and technical progress

Farms carry out innovation and imitation processes (Conforti, 2017), in order to improve their productivity θ_{it}, i.e. the amount of food they are able to produce for a given level of soil and labor. The ability of farms to enhance their productivity is indeed one of the key-mechanisms of the model (Coomes et al., 2019). Gains in productivity in smallholder settings arise through several channels, including: i) improved cultivars and seed varieties, enhanced fertilizers and pest management practices; ii) ameliorated land management and soil quality; iii) changes in operational routines, including the acquisition of new skills and of management

[2] In this model version, capital is not explicitly represented. While the introduction of new capital has advanced agricultural inputs (Belton et al., 2021), the share of capital to agricultural income is relatively contained in smallholder settings (up to 30-40% in developed countries, even lower in developing ones). Capital expenditures, around 40% of the total, remain constant across crops and farming systems. Smallholder farming systems are typically characterized by phenomena like the rental and sharing of capital (Diao et al., 2018; Sims and Kienzle, 2017; Mrema et al., 2014). We believe that omitting capital does not significantly alter the model's dynamics for the purpose of this study.

capabilities (Nelson and Winter, 1973).

Innovation: Innovation is modeled as a two-step process. Each farm thus devotes a share of its previous period revenues to the costly activity of searching for productivity-boosting alternatives (Equation B.2). The amount of resources devoted to searching activities - which proxies both time-consuming search efforts for alternative techniques and training, as well as actual saving for purchases of new inputs - augments the probability of getting an innovation, whose probability is determined via a Bernoulli trial (Equation B.3). The uncertainty in the first stage reflects the idea that the innovative efforts might not be successful due e.g. to insufficient knowledge or lack of key inputs.

If farms successfully innovate, they increase their productivity by an amount which is randomly drawn for a symmetric Beta(α, β) distribution. The support of the Beta(α, β) distribution, which regulates the set of technological opportunities farms may capture, lie in $[\theta_{min}, \theta_{max}]$, with $\theta_{min} < 0$ and $\theta_{max} > 0$. The negative part of the support represents failed innovation, which are relatively common in the agricultural sector (Peters et al., 2018; Razanakoto et al., 2018). The uncertainty in the second stage captures instead the notion that the actual impact of innovative practices cannot be know ex-ante by agents. Especially in smallholder farming systems, a new input (e.g., an improved quality of seeds) might not work well in a given soil, just like changes in organizational schemes and routines might turn out to be highly inefficient (see e.g. Kephe et al., 2022; Thierfelder and Wall, 2011). Thus, larger innovation expenditures have no short-run implications in terms of the sign and the size of actual productivity gains.

Imitation: A similar mechanism governs imitation, an extremely common practice in smallholder farming systems. It involves social networks, peer-learning mechanisms and adoption of techniques employed by competitors (Beilin et al., 2013; Manson et al., 2016; Conley and Udry, 2010; Bandiera and Rasul, 2006). In presence of set-up costs and barriers to imitation (MacLeod et al., 2005; Brenner, 2006), the amount of resources devoted to imitation (Equation B.4) increases the chances of success (Equation B.5). Given the high relevance of spatial proximity - alongside with other factors, such as physical infrastructures and social networks - for imitation patterns (Tirkaso and Hailu, 2022; Pomp and Burger, 1995; Moss et al., 2000), the farm gets closer, in terms of productivity, to the most productive farm within a given distance (Equations B.6 and B.8)

Within-farm learning: Imitation between different firms is complemented by ‘within-firm learning’: farms owned by the same firm costlessly get closer to the most productive farms among those owned (see Equations B.7 and B.8), mimicking top-down transfer of knowledge (Swinnen, 2007; Tittonell et al., 2010; Swinnen, 2007).

4.1.2 Food market

Demand for food is exogenous, and grows linearly (Equation B.9), mimicking global population growth (Roser et al., 2013) and increasing standards of living. Each firm collects the food produced by the farms it owns, sells the total output on a centralized market, and redistributes profits to owned farms (Manson et al., 2016). The centralized market represents a stylized food supply chain characterized by monopsony, a fair approximation of small-scale agricultural setups (Sivramkrishna and Jyotishi, 2008), typically dominated by large processing food companies acquiring from a variety of small producers. Food price is thus unique, and reacts to supply-demand imbalances (Equation B.10).

Firms market shares MS_{zt} evolve according to a quasi-replicator dynamics (Equation B.11), along the lines of the evolutionary literature both in industrial dynamics (e.g. Dosi et al., 2010; Chiaromonte and Dosi, 1993), as well as in agricultural economics (Beard and Purcell, 2000; Meng and Zhou, 2022). Firms compete on two factors: a proxied measure of firm efficiency (Equations B.12 and B.13, as large food-processing companies tend to favour highly productive producers, capable of delivering substantial quantities (Sivramkrishna and Jyotishi, 2008; MacDonald et al., 2018)) and their ability to consistently serve the demand they face, as measured by unfilled demand (the discrepancy between the demand corresponding to their market share and the quantity effectively sold; Equations B.12 and B.14).

A key feature of the model is represented by the interaction between innovative behavior and market dynamics. By ameliorating their farms' productivity, firms are capable of producing higher quantities more efficiently, and can thus boost their market shares through the efficiency channel (Equation B.13). Higher market shares will in turn increase the probability to further innovate - via augmented revenues - in a process of self-reinforcing positive feedbacks. As such, the model display dynamic increasing returns to scale. On the other hand, by expanding their production, firms exposure to frictions in labor and transportation markets increases (Prus and Sikora, 2021; Bacior and Prus, 2018), thereby impairing their ability to deliver the expected output and causing market shares to decline. Such frictions can be substantial in rural areas (Cook and Cook, 1990; Roberts et al., 2017; Thacker et al., 2019), and are captured by the unfilled demand channel (Equation B.14).

4.1.3 Production adjustment

There are several strategies that firms can put in place in order to expand - or reduce - their production.

- *Labor adjustment*: First, firms decide how much labor to hire (or fire), fastly reacting to over and under-production (as measured by unfilled demand; Equation B.15).

- *Acquisition of defaulted farms*: Second, firms who persistently under-produce can expand their production by employing additional plots of land. This can happen through the acquisition of farms on sale. In fact, defaulted firms, because of negative liquid assets (Equation B.23) or insufficient market shares, sells their owned farms through a second-best auction. The likelihood of submitting a bid is contingent upon the perceived under-production, as measured by the unfilled demand observed in the most recent periods (Equation B.18). In the event of an unsuccessful auction, the farm is abandoned (as noted by Gellrich et al., 2007) and the soil on which it operated gradually reverts to a forested state.

- *Deforestation*: Third, farms who systematically do not meet their production needs, may acquire novel plots of land by deforesting a close virgin land. The probability of deforesting depends again on the perceived under-production (Equation B.19). Forests are then turned into highly productive farms (Haddaway et al., 2014), reflecting the productivity gain entailed by the usage of a virgin soil (Barbier et al., 2010).

4.2 Conventional *versus* sustainable in the model

In this model version, we introduce two distinct production techniques, allowing firms to dynamically switch between them. Technical change operates along these paradigms, leading to distinct and endogenous dynamics in the evolution of farm productivity and innovation processes.

As described in Section 3, conventional techniques are usually more productive and characterized by a higher innovation potential. We thus allow conventional farms to draw innovation gains (IN_{it}) from a larger support with respect to sustainable ones. Formally, the support of the symmetric $Beta(\alpha, \beta)$ - typically both lower and upper bounded - is rescaled to $[\theta^C_{min}, \theta^C_{max}]$ for conventional farms and to $[\theta^S_{min}, \theta^S_{max}]$ for sustainable ones, with $\theta^C_{min} = \theta^S_{min}$ and $\theta^C_{max} > \theta^S_{max}$ (cf. Figure 1). However, the net extraction of soil nutrients from the ground operated by conventional farms leads in the long-run to productivity losses due to soil degradation. Sustainable farms are characterized thus by lower yields in the short run, but are not subject to soil depletion as they balance inputs and outputs in terms of soil nutrients. We here concentrate solely on human-induced soil depletion (Oldeman et al., 2017)), a type of degradation closely associated with the intensity of agricultural activities.[3] Thus, Equation B.8 for the overall dynamics of farm productivity θ_{it} becomes

$$\theta_{it} = (1 - \mu_{IM} - \mu_W)\theta_{it-1} + \mu_{IM}\theta^{IM}_{it} + \mu_W\theta^W_{it} + \mathrm{IN}_{it} - \mathrm{D}_{it} \tag{1}$$

where θ^{IM}_{it} and θ^W_{it} are the productivities of the imitated farms (for imitation tout-court and within-farm learning, respectively), IN_{it} is innovation gain, and μ_{IM} and μ_W are parameters tuning the strenght of imitation and within-farm learning effects. Lastly, soil degradation D_{it} impacts negatively on farm productivity.[4]

Capturing global soil depletion rate phenomenon originated by land-use change poses serious challenges, due to heterogeneous scale and spatial effects. The effects of soil degradation, leading to stagnating or even descending trends in agricultural yields are nonetheless well documented by empirical studies in several regions (Borrelli et al., 2017; Ray et al., 2012), and highly related to unsustainable land management (Mbow et al., 2017). In the model, soil degradation depends on the cumulative amount of time periods T^c_i in which the farm i has been producing in a conventional regime, and evolves according to a logistic function (see Equation 2 and Figure 1B):

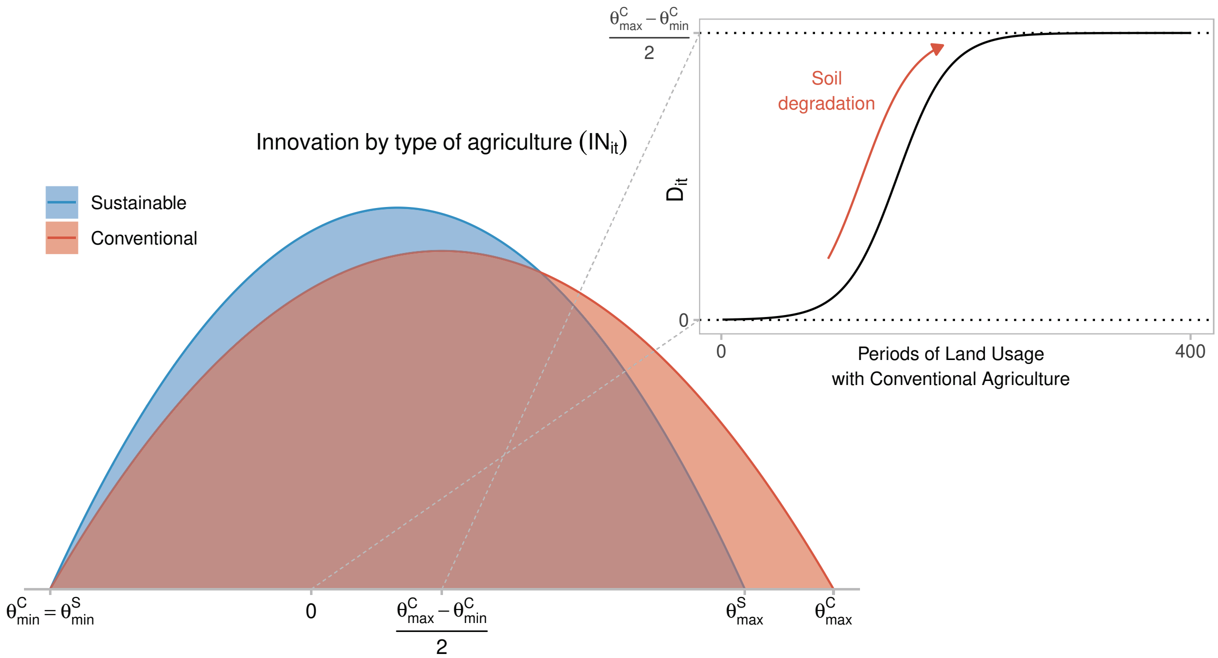
$$\mathrm{D}_{it} = A + \frac{K - A}{1 + e^{-b(T^c_i - M)}} \tag{2}$$

where b controls the growth rate, and M shifts the logistic on the horizontal dimension, while A tunes the lower asymptote (in our case, clearly equal to 0), and K the upper asymptote. As shown Figure 1B, we typically

[3] Soil depletion due to non-human induced factors persist even in sustainable farming. However, nutrients and carbon replenishment ensures the mitigation of chemical soil degradation, which is human-induced and it is the most diffuse (Tittonell et al., 2005). Other forms of soil depletion (e.g. physical degradation induced by natural hazards or atmospheric agents) can be nonetheless analyzed in the model, in the form of exogenous climate shocks - see the analysis in Coronese et al. (2023).

[4] Since - when modeling innovation - we do not distinguish between improvements to soil and advancements in inputs quality or in organizational routines, we coherently treat soil degradation as affecting the entire farm productivity.

Figure 1: Soil productivity dynamics in different agricultural regimes.



Note: Different innovation supports for conventional and sustainable farming, along with graphic representation of soil degradation mechanism.

parameterize the logistic function in a way that allow us to replicate such stagnating dynamics: the maximum loss is set equal to the average productivity gain for conventional farms, potentially implying a plateau in farm productivity. [5] The logistic specification has the advantage of being highly flexible, allowing us to experiment with different scenarios of soil depletion by tuning its parameters (see Section 5.5).

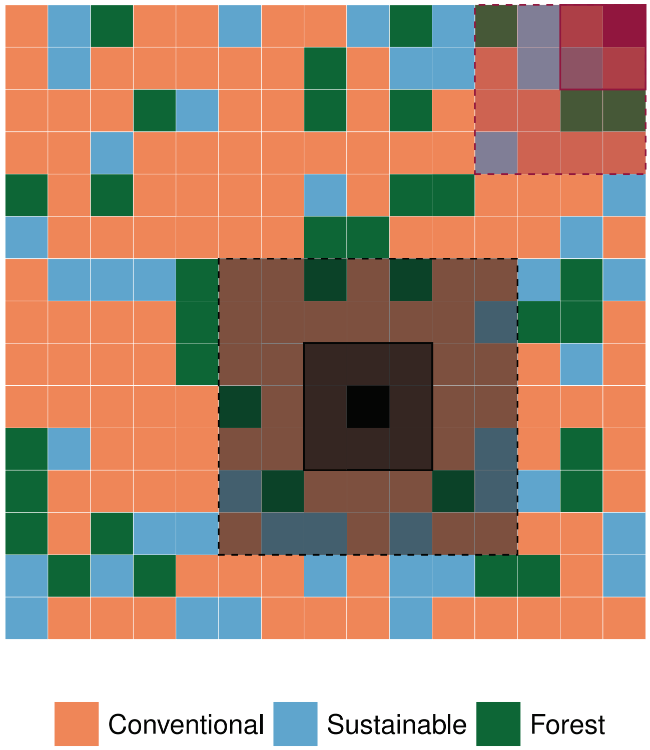
Given the trade-off between the short-run higher yields granted by conventional farming and long-run losses associated with soil degradation, how do firms choose between the two regimes? Agents can switch between sustainable and conventional farming according to their perceived productivity, employing a discrete choice model (along the lines of Brock and Hommes, 1997). If a firm switch regime of agriculture, all the owned farms switch accordingly; larger firms have thus more influence on aggregate dynamics with respect to smaller ones. Each firm observes the performance of it neighbors within a given distance d^s from each owned farm. This defines the observational horizons and the sets of neighboring conventional and sustainable farms, C_{zt} and S_{zt} respectively (cf. Figure 2). [6] Consequently, larger firms can count on larger information sets. Firm z assesses the performance of its neighbouring sustainable (S) and conventional (C) farms considering their average output per worker γ^S_{zt} and γ^C_{zt}:

$$\gamma^S_{zt} = \frac{1}{\#(S_{zt})}\frac{1}{m}\sum_{k\in[t-m,t]}^{i\in S_{zt}}\frac{Y_{ik}}{L_{ik}} \qquad \gamma^S_{zt} = \frac{1}{\#(C_{zt})}\frac{1}{m}\sum_{k\in[t-m,t]}^{i\in C_{zt}}\frac{Y_{ik}}{L_{ik}} \tag{3}$$

[5] In a conservative spirit, we further assume that losses from soil degradation are entirely reversible through soil nutrients reintegration: thus, when a farm becomes sustainable, soil regeneration occurs as it walks imaginatively backwards on the logistic curve (negative values of D_{it}). Indeed, degraded lands fully recovering strongly depend on farmers' technological choices (Sanchez et al., 1997; Tittonell et al., 2010), but is also linked to the timing of the action (Pang and Letey, 2000).

[6] C_{zt} and S_{zt} include the farms belonging to the observer firm.

Figure 2: Different observational horizons ($d^s = 1$ and $d^s = 3$) from distinct locations on the lattice.



where m is the observational time window along which farms compute averages (or memory), Y_{ik} is farm-level output, L_{ik} is farm-level employment, and $\#(S_{zt})$ and $\#(C_{zt})$ are the cardinalities of the sets of neighboring sustainable and conventional farms, respectively. We then define the two quantities Γ^S_{zt} and Γ^C_{zt} governing the switching process:

$$\Gamma^S_{zt} = \frac{exp\left(\tau \cdot \gamma^S_{zt}\right)}{exp\left(\tau \cdot \gamma^S_{zt}\right) + exp\left(\tau \cdot \gamma^C_{zt}\right)} \qquad \Gamma^C_{zt} = \frac{exp\left(\tau \cdot \gamma^C_{zt}\right)}{exp\left(\tau \cdot \gamma^S_{zt}\right) + exp\left(\tau \cdot \gamma^C_{zt}\right)} \tag{4}$$

where τ is a parameter governing the intensity of switching. A conventional firm (type C) will thus attempts to switch if and only if $\Gamma^S_{zt} > \Gamma^C_{zt}$, that is when it observes sustainable farms (type S) performing better on average than conventioanl ones. Actual switching is then determined trough a random draw from a Bernoulli with mean $\chi^S_{zt} = 2\Gamma^S_{zt} - 1$.[7] Clearly, the converse holds true for a sustainable firm. Thus, the higher the observed difference in performance, the higher the probability of switching. Finally, firms are allowed to switch only every q periods.

Firms are thus endowed with different degrees of bounded rationality: in the time dimension, as they remember neighbours performances only for a limited amount of time (m), and in the spatial dimension (Moss et al., 2000; Pomp and Burger, 1995), as they observe only within a limited observational horizon (d^s). By assuming that agents are able to observe output per worker of neighboring farms, we implicitly assume that they perfectly observe each farm productivity. In Section 5.3, we replace output per worker with output only -

[7]This rescaling is operated in order to ensure that $\chi^S_{zt} \in [0, 1]$. Indeed, when $\Gamma^S_{zt} > \Gamma^C_{zt}$, it follows that $\Gamma^S_{zt} \in [\frac{1}{2}, 1]$

as indicated by behavioral studies about imitating factors among farmers in proximity (Schmit and Rounsevell, 2006) - thus introducing an additional level of bounded rationality (Equation B.24).

5 Results

After detailing the model parametrization and the simulation protocol in Section 5.1, we initially outline the main endogenous scenarios arising in the model, and the key mechanisms influencing the success or failure of transitioning towards a sustainable regime (Section 5.2). Following an examination of transition dynamics in the baseline model (Section 5.3), we investigate the impact of behavioral (Section 5.4), environmental (Sections 5.5 and 5.6), and institutional factors (Section 5.7) on facilitating or impeding the transition. Lastly, we utilize the model in Section 6 to assess the effectiveness of specific regulation-based and market-based policies.

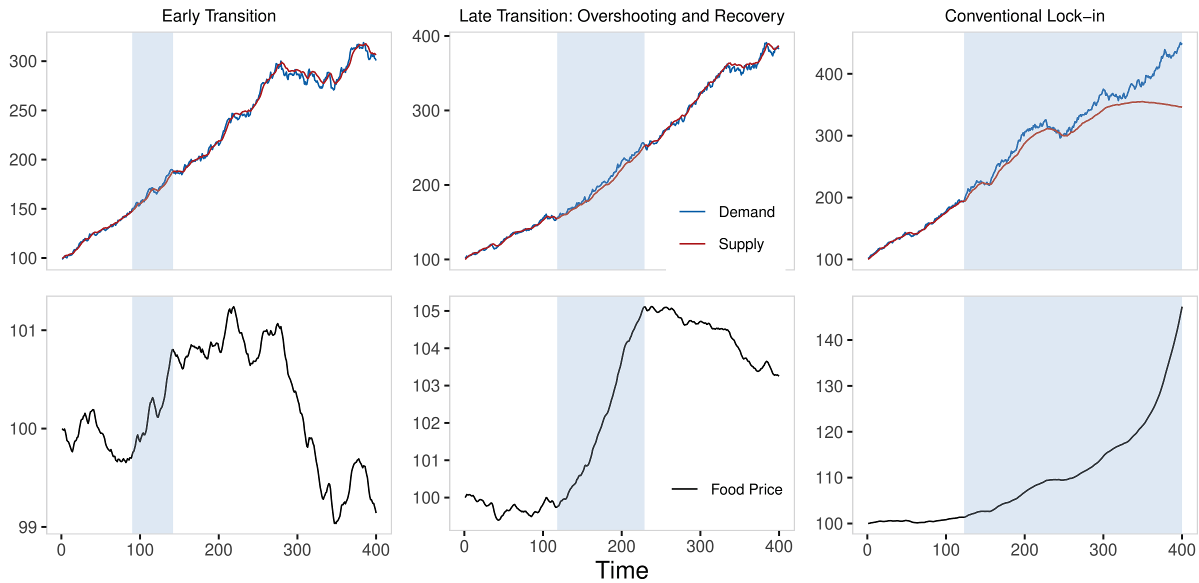
5.1 Model setting, parameterization and simulation setup

As it is typically the case in agent-based computational economics literature, agriLOVE does not allow for analytical, closed-form solutions (for a discussion, see Fagiolo and Roventini, 2017; Fagiolo et al., 2019). We then perform extensive Monte Carlo simulation exercises to study the properties of the stochastic processes governing the co-evolution of micro- and macroeconomic variables. The model is simulated for 400 periods (plus a transient of 100 periods), interpreted as quarters, thus implying a simulation horizon of one century. Results are reported as Monte Carlo averages - unless differently specified.[8]

The model is initialized and parameterised to match realistic shares and dynamics typical of smallholder farming systems. Regarding the selection of parameter values, our simulation approach adopts a method akin an indirect calibration strategy (Fagiolo et al., 2019). Details on baseline calibration based on robust empirical evidence within smallholder farming systems, sensitivity analysis regarding alternative calibrations, and model initialization can be found in Coronese et al. (2023). Additionally, we initialize the model with 25% sustainable farms and 75% conventional ones, randomly distributed across the grid, mirroring global estimates of sustainable agriculture diffusion (Willer and Lernoud, 2017; de la Cruz et al., 2023). Acknowledging that the definition of sustainable farming in this paper is broader than organic farming alone - which is often the focus of most reliable estimates - we adopt, among various estimates, the most optimistic one. Moreover, we set sustainable farms to be initially 30% less productive on average, reflecting the observed current productivity gap between sustainable and conventional techniques (Ponisio et al., 2015; McKenzie and Williams, 2015; de la Cruz et al., 2023). Lastly, reliable estimates for the varying innovation potential - i.e. the difference between the supports of the distributions from which innovations are drawn - between the two agricultural regimes are even harder to retrieve. Consequently, we opt for a relatively high differential of 17%, aligning with a conservative scenario. Timeline of the events, parameters and initialization assigned values are reported in Appendix A.

[8] As already acknowledged by Meadows et al. (1972) and Meadows and Randers (2012), also our simulation in each scenario are predictions "only in the most limited sense of the word", and must be interpreted only as indications of the system's behavioral tendencies.

Figure 3: Transition, overshooting and lock-in scenarios in the model.



Note: Three different single runs of the model, exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming, overshooting (or late transition) and conventional lock-in. For each run, distance between total demand and supply and food price dynamic are shown. Shaded areas correspond to periods of insufficient food supply.

5.2 Transition dynamics

Being boundedly rational, agents are generally unaware of the long-run productivity and soil degradation dynamics implied by their technical choices. As already pointed out, agents infer the potential success of a technical regime observing their own performances, together with that of their neighbors. Generally, conventional firms will gain market shares in the early stages of the simulations, driven by higher innovation potential and, consequently, higher output and market shares. When soil degradation becomes an impeding factor, the system will be more or less capable to favor a transition towards sustainable farming, preventing loss of farm productivity and favoring food security, depending on the competitive advantage accumulated by conventional firms, their diffusion and other environmental/behavioral factors. Typically, each run of the model can evolve according to one of the three scenarios exemplified in Figure 3, which closely mimic those present in global models with environmental boundaries (e.g. *World3* in Meadows and Randers, 2012). The relative prevalence of these three scenarios can be influenced by different factors, and derive from the emergence of positive and negative tipping points. We shall explore their relevance in the Results section.

- *Rapid transition*: Under the most optimistic circumstances, sustainable farming will spread gradually in the spatial grid as the first signs of soil degradation - in the form of insufficient supply - become evident to agents, causing a rapid transition to a sustainable regime. As visible in the left quadrants of Figure 3, in this case food supply is capable to keep the pace of food demand, and food shortage is almost absent, as testified by the very small and temporary increase in food price.
- *Late transition - Overshooting and recovery*: However, several circumstances which we shall explore (e.g.

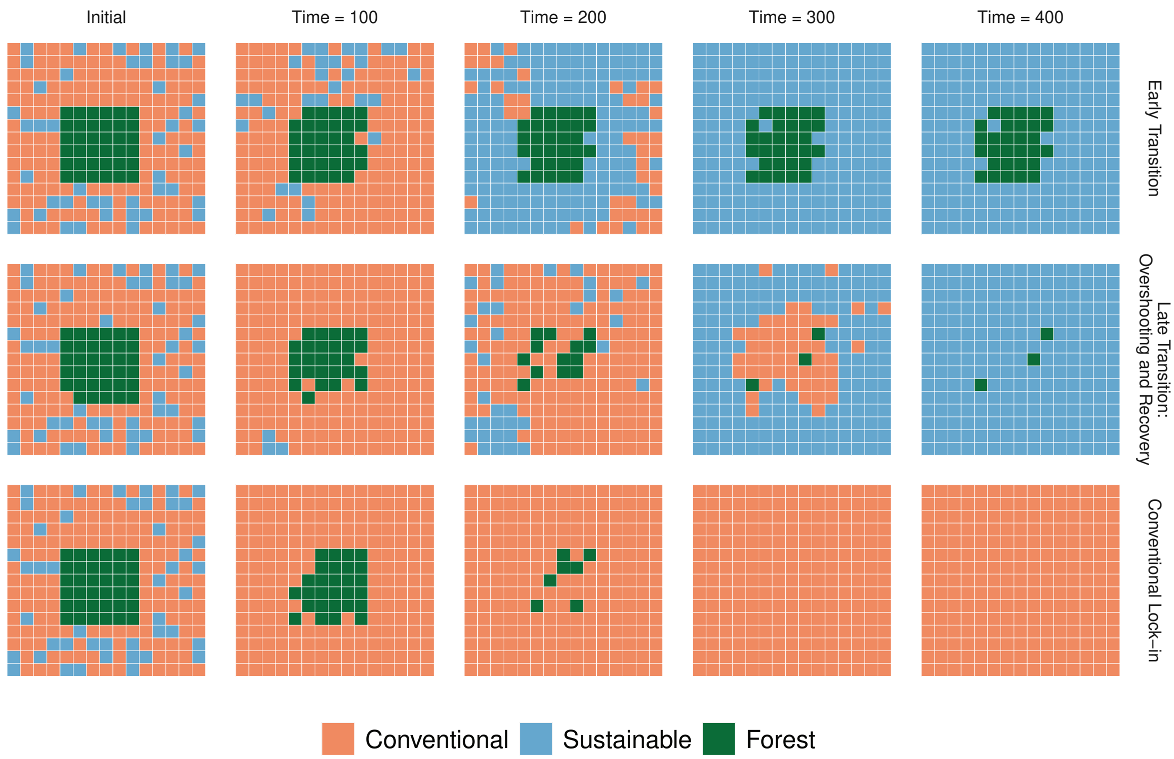
recourse to deforestation) can delay or prevent sustainable transition to take place. In the central quadrants, the system is still able to operate a transition, but conversion of conventional firms to sustainable ones is lagging with respect to soil degradation. In this case, the system is in a typical "overshooting" scenario, where even when losses from soil degradation becomes evident, agents do not timely switch, because of coordination failures, misaligned incentives or imperfect information. This results in a prolonged period in which food demand is not entirely satisfied, reflected by a food price which constantly increases for an extended time span, until damages due to soil degradation are gradually reabsorbed.

- *Conventional lock-in*: The most pessimistic scenario, the conventional lock-in, is depicted in the right quadrants of Figure 3. In this case, the competitive advantage initially gained by conventional firms prevents the spreading of sustainable ones, with agents fully switching to the former, without considering future losses associated with increased soil depletion. Losses from soil degradation accumulates, leading to a slowed growth in farm productivity; agents react by hiring more workers and deforesting until losses becomes binding and food production reaches a plateau. In a world characterized by increasing demand, this causes a persistent upsurge in food scarcity and food price. The increase of food price in presence of soil degradation has indeed been abundantly documented in the literature for different types of crops (Noel, 2015; Kopittke et al., 2019; Lal, 2004; Scherr, 1999; Brown and Wolf, 1984).

Beside transitioning to a sustainable type of farming, there are several strategies that firms can put in place to counterbalance - in the short run - the loss of productivity. As outlined in Section 4.1.3, the most common are hiring more workers, acquiring/renting new plots and deforesting virgin lands (Wibowo and Byron, 1999). These activities boost production in the short term, but they are bound to become progressively ineffective, due to diminishing return to labor, or to the limited amount of virgin lands and their environmental value. By masking the effects of soil degradation, these actions can significantly delay or even prevent sustainable transitions to happen. Figure 4 shows the spatial diffusion of the two agricultural regimes in the three scenarios depicted in Figure 3. It illustrates not only the harmful effects of conventional farming on forestry (as widely documented in several empirical works, e.g. Tachibana et al., 2001; Tinker et al., 1996; Grau et al., 2005), but how forests' availability can delay sustainable transition - or, conversely, how a fast transition is crucial factor in preserving the stock of forestry. As a matter of fact, the middle row in Figure 4 pictures a late transition, where conventional farms cluster around forest land, being deforestation a viable and effective way to mitigate loss of in-farm productivity (Marchand, 2012). We shall explore in detail the role of these *masking factors*.

Transition dynamics in the model are complex phenomena, pulled between two "attractors": conventional lock-in and sustainable transition, rapid or coupled with overshooting. In what follows, we investigate the multi-level interaction of social and technological elements within such transition pathways (Foxon, 2011), exploring how environmental, institutional and behavioral factors might favor or impede transition to a sustainable regime.

Figure 4: Spatial grid view of transition, overshooting and lock-in scenarios in the model.



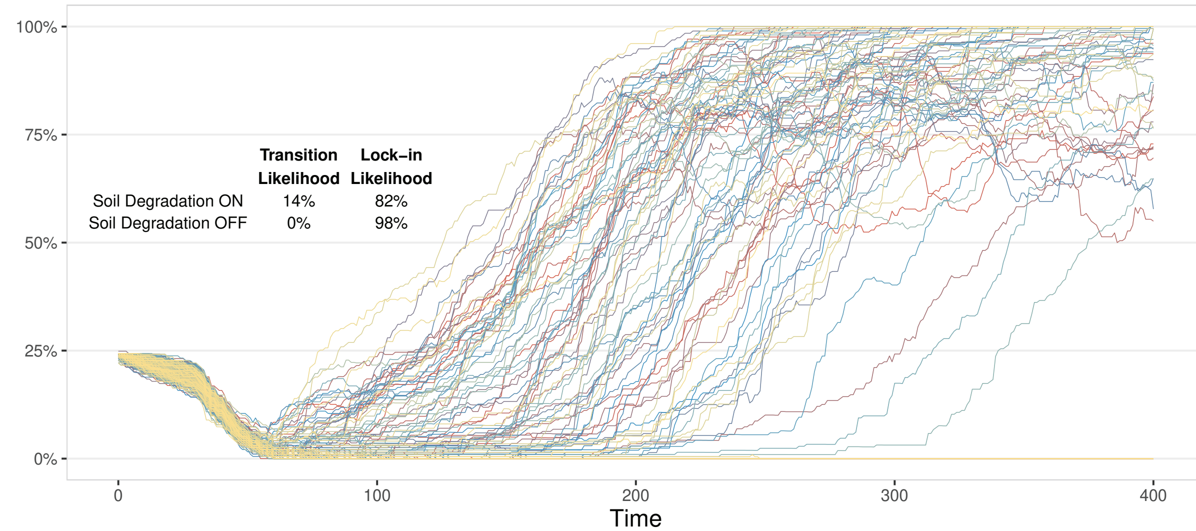
Note: Three different single runs of the model (same as in Figure 3), exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming, overshooting (or late transition) and conventional lock-in. For each run, spatial distribution of forests, sustainable and conventional farms are shown at distinct points in time.

5.3 Baseline

We begin by investigating the behavior of the baseline configuration of the model (see also Coronese et al., 2023). Figure 5 shows the evolution of the share of sustainable farms in each Monte Carlo run. Without any supporting policy, the system is unable to systematically achieve the transition to sustainable agriculture, with a likelihood of only 14.2%. This suggest that in absence of adequate policies, the system's capacity to diffuse sustainable agricultural practices is limited. By contrast, the probability of a conventional lock-in is substantially higher (81.8%). In the rare cases in which a transition occur, the share of sustainable farms evolves according to a typical S-shaped diffusion curve, although at different speeds and at distinct points in time. Intermediate cases - or *failed transitions* - are also possible, in which neither a transition nor a lock-in are observed (4%). Such a pessimistic picture is consistent with what is observed in the real world. In the Global South, where the majority of smallholder farming systems are located, the interactions among heterogeneous farmers are often not sufficient to provide effective collective coordination leading to the adoption of sustainable farming practices in the absence of national programs and *ad hoc* agricultural policies (Barrett et al., 2017). These results echo aspects of the *Limits to Growth* debate and are consistent with evolutionary approaches to eco-innovations, emphasizing the clear role of policies and institutions (Freeman, 1996; Cecere et al., 2014).

Table 1 delivers a more comprehensive picture, displaying summary statistics for transition dynamics using

Figure 5: Share of sustainable farms by single Monte Carlo Run.



Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Lock-in probability is defined as the share of Monte Carlo runs with final share of sustainable farms equal to 0. 500 Monte Carlo replications.

both output per worker (Equation 3) and output only (Equation B.24) as proxies of neighbours performance in Equation 4. Overall dynamics in presence of soil degradation are robust to the usage of output alone as alternative proxy, albeit less clear-cut. The relative majority of runs end up in a lock-in scenario, although transition and lock-in likelihoods are lower (from 14.2% to 11% and from 81.8% to 50.2%, respectively), while we observe a larger likelihood of intermediate cases (38.8% against 4%). Consistently, when firms needs to rely on an imperfect proxy such as the output for observing farms productivity, transitions tend to be slower, with an average transition length which is almost doubled with respect to the output per worker scenario. Despite the interesting dynamics introduced by this additional level of bounded rationality, and even if there is evidence that farmers frequently observe competitors' output to infer their productivity (McCann, 1995; Bandiera and Rasul, 2006), we maintain in what follows output per labour as our baseline proxy, as it allows us to explore and explain more neatly model's outcomes. Simulating an identical environment without soil degradation, or with minimal degradation, is a valuable exercise for investigating the functioning of the discrete choice module under modest environmental pressure. The 97.8% probability of conventional lock-in in the "Soil Degradation OFF" scenario (using output per worker as a proxy) indicates that in the absence of any adverse effects resulting from conventional techniques, agents will surely choose, at least in the long run, the higher-yielding production technique. Notably, the amount of remaining forests (42%) without soil degradation aligns with figures obtained by extrapolating recent trends for forest coverage in low-income and smallholder farming countries.[9] Also when using output as a proxy, the majority of cases still anticipate convergence to the most efficient technique. This type of lock-ins are typically present in spatially-explicit path dependent models, where the presence of

[9] Extrapolating linear trends over the period 1990-2020 and projecting them over one century, the predicted share of remaining forests for distinct groups of countries is as follows: IDA countries 40%, low-income countries 44%, lower-middle-income countries 58%. Data also indicate the absence of marked regional heterogeneity: Arab World 18%, Eastern and Southern Africa 44%, Western and Central Africa 57%, Sub-Saharan Africa 48%, Latin America and Caribbean 58%.

Table 1: Transition, lock-in and intermediate cases probabilities using both output per worker and output as performance proxy, with and without soil degradation.

Output per worker

	Scenarios Likelihood			Transition Dynamics			Macro Variables	
	Transition	*Lock-in*	*Intermediate*	*Start Date*	*End Date*	*Length*	*Food Scarcity*	*Remaining Forests*
Soil Degradation ON	14.2%	81.8%	4%	36.5%	68.1%	31.6%	16.4%	9.9%
Soil Degradation OFF	0%	97.8%	2.2%	-	-	-	0.05%	42.1%

Output

	Scenarios Likelihood			Transition Dynamics			Macro Variables	
	Transition	*Lock-in*	*Intermediate*	*Start Date*	*End Date*	*Length*	*Food Scarcity*	*Remaining Forests*
Soil Degradation ON	11%	50.2%	38.8%	36.3%	91.2%	54.8%	10.1%	17.6%
Soil Degradation OFF	0%	73%	27%	-	-	-	0.05%	43.4%

Note: Output per worker (Equation 3) and output (Equation B.24) used as performance proxy in Equation 4. Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Lock-in probability is defined as the share of Monte Carlo runs with final share of sustainable farms equal to 0. Start date is equal to the latest time step at which the share of sustainable farms surpasses 10%, while end date to the earliest time step at which it surpasses 90%, both expressed as percentage of simulation length. Length is defined as the difference between start and end date, expressed as percentage of simulation length. Food scarcity is given by the share of time steps with excess demand larger than 5%. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry. Transition dynamics are averaged across runs which end up in a successful transition. Macro variables are Monte Carlo means. 500 Monte Carlo replications.

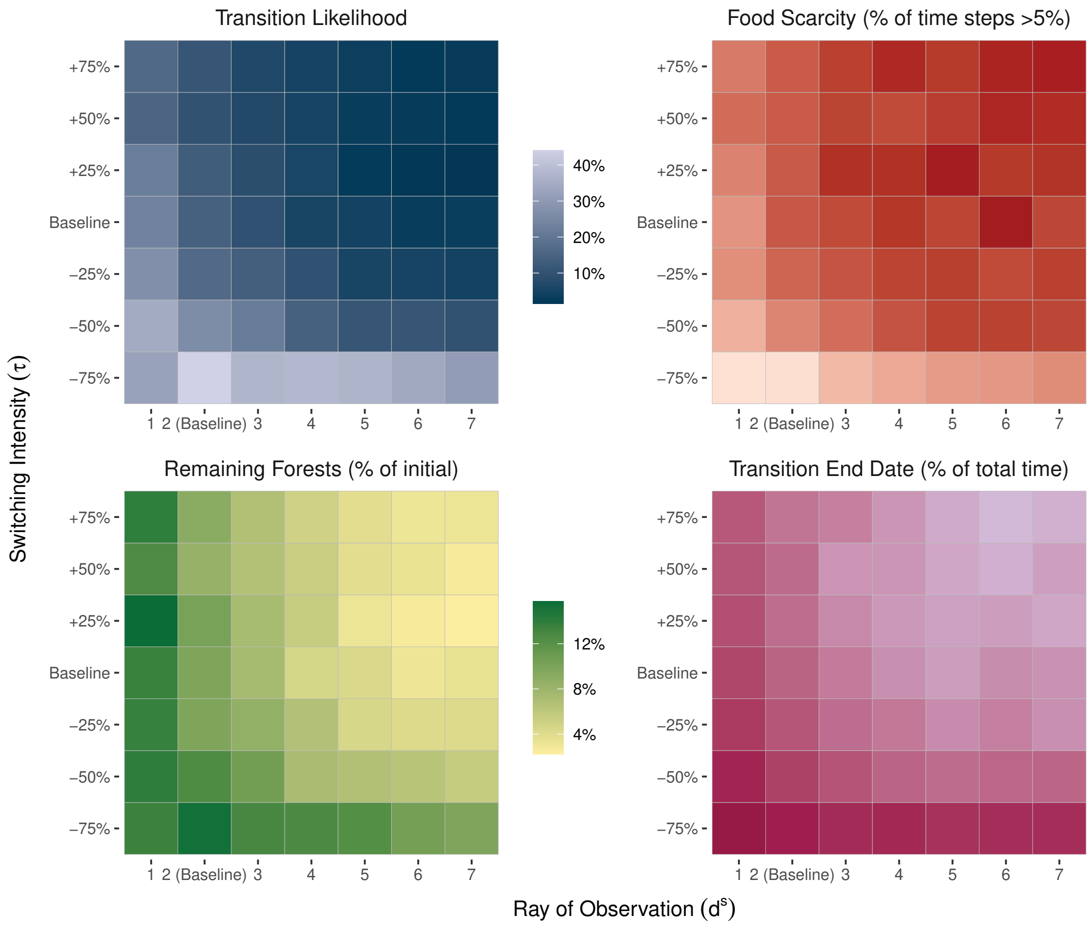
increasing returns creates a bandwagon effect by increasing the profitability of the dominant innovation as the number of adopters increases (Abrahamson and Rosenkopf, 1997; Cecere et al., 2014). Moreover, when soil depletion is not present, the demand pressure on the system is also much lower, resulting in the absence of food scarcity and, more remarkably, into a higher share of remaining forests.

5.4 Behavioral factors

Agents in the model exhibit bounded rationality across various dimensions. Specifically, agents observe only the performance of their neighbors within a limited horizon d^s, and they can be characterized by a variable propensity to switch, denoted as τ in Equation 4. We investigate how these two parameters influence the propagation of the soil deterioration signal in the system and, consequently, either promote or impede transition dynamics. The findings are presented in Figure 6.

We begin by commenting the impact of varying the propensity to switch (τ), when the observation radius (d^s) is fixed at its baseline value. The parameter is explored within the range typically utilized in the literature for similar discrete choice models (e.g., Brock and Hommes 1997). The propensity to switch significantly influences the promotion of transition (and reduction of lock-ins) only when set to very low values (upper-left quadrant in Figure 6). In other words, if the system is inhabited by agents with particularly conservative attitudes, the likelihood of sustainable actors surviving without converting to conventional techniques increases, thereby raising the probability of a subsequent transition. This interpretation finds further support in the results obtained from experimenting with heterogeneous attitudes to switch between sustainable and conventional firms, as depicted in Figure C.2. When sustainable firms exhibit a lower propensity to switch regimes (compared to our baseline value of $\tau = 1$), while conventional ones are more inclined, we observe an increased likelihood of transition, steadily

Figure 6: Heat-maps for different observational horizons d^s and attitudes to switch τ.



Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, averaged across runs which end up in a successful transition, expressed as percentage of simulation length. Food scarcity is given by the share of time steps with excess demand larger than 5%. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 500 Monte Carlo replications.

rising with the deviation from the baseline attitude to switch. Sustainable firms with a low attitude to switch tend to refrain from adopting conventional techniques in the early stages of the simulation, while conventional ones are quicker to switch when sustainable farming becomes more productive. Coherently, conducting the opposite exercise (making sustainable firms more prone to switch while making conventional ones less prone) indeed results in lower chances of transition, albeit less monotonically. Empirical instances of low values for τ are observable in some smallholder farming settings, where the inclination toward changes and the adoption of conventional production techniques are typically low (Alene et al., 2000). In remote and marginal settings, farmers often view new production techniques as challenging to apply in their contexts (Conley and Udry, 2010). This perception, combined with a low propensity to switch, impedes the adoption of new production techniques (Emerick et al., 2016). Conversely, medium and high propensities to switch appear to exert minimal or no influence on transition dynamics.

Varying the observation radius d^s— while keeping τ fixed at its baseline value — produces even more clear-cut outcomes. The likelihood of transition markedly diminishes with larger observational horizons, and the effect appears to be slightly non-linear. When the information is already relatively high, the probability of transition becomes so low that further increasing the observational horizon has only a marginal impact on transition behavior. When observed accurately, the initial comparative advantage of conventional firms motivates sustainable ones to switch. Paradoxically, having more information hinders sustainable transition and significantly raises the likelihood of a conventional lock-in. This outcome underscores the dynamic nature of information sharing in the model. Almost perfectly observing the performance of both techniques — without any foresight and with purely adaptive behavior — tends to result in the adoption of the production technique most productive in the short run, i.e., the conventional one. This aligns with findings in seminal works on information networks in agriculture (Roling, 1988; Demiryurek et al., 2008), illustrating how a lack of foresight leads to the adoption of production techniques offering higher short-run gains.[10]

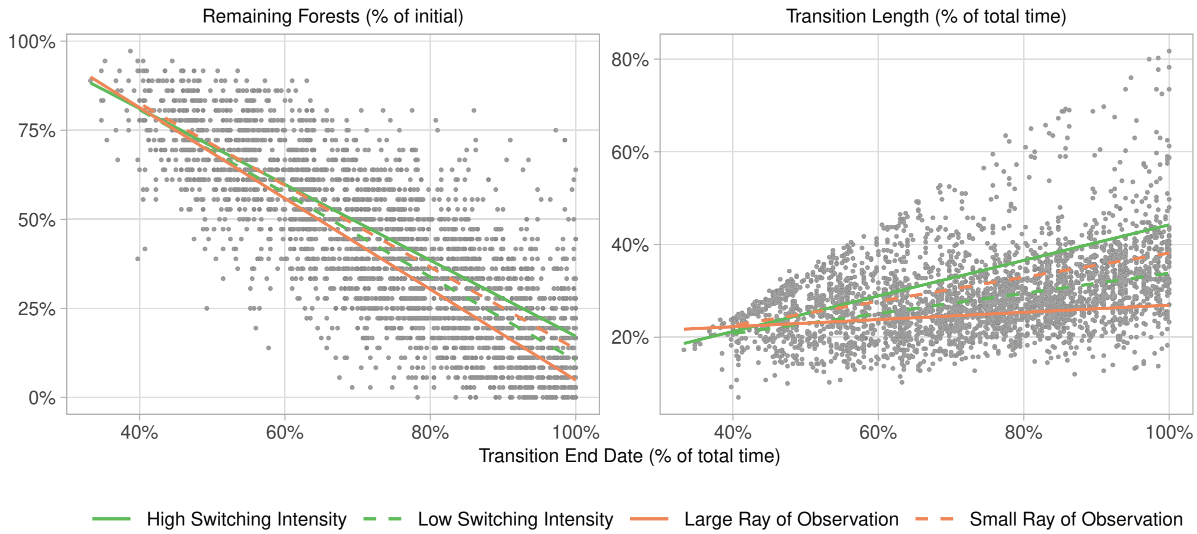
The interaction between the observational horizon and the propensity to switch unveils interesting patterns: a greater inclination towards switching translates to progressively less information required to yield very low probabilities of transition. Typically, the lowest probabilities of transition occur with extensive observational horizons and when agents are more disposed to adopt a different production technique. The combination of abundant information and heightened responsiveness to it seems to jeopardize the survival of sustainable firms and inhibits the timely dissemination of soil degradation signals across the system. Coherently, the evolution of food scarcity (upper-right quadrant in Figure 6) closely reflect the patterns described for production technique adoption. In terms of transition timing (lower-right quadrant in Figure 6) higher values for switching intensity and, more surprisingly, observational horizon are associated with earlier transitions. The latter is likely due to the fact that only transitions which happen very much on time with respect to the evolution of soil degradation are possible in these model set-ups. Deforestation dynamics (lower-left quadrant in Figure 6) are the result of the interaction between the likelihood of transition and the speed at which it takes place. This happens both because sustainable firms do not deforest, and because lock-in scenarios are characterized by higher demand pressure. A faster transition towards sustainable regimes can prevent the strong recourse to deforestation from conventional firms, in the attempt to contrast stagnating yields by cultivating virgin areas (see Figure 4). As a matter of fact, transition end dates appear to monotonically decrease along both switching intensity and ray of observation (Figure C.1), suggesting that a higher level of agents' rationality decreases the likelihood of an overshooting scenario.[11]

The left panel of Figure 7 showcases in detail the strong negative relationship linking transition length (or overshooting likelihood) and share of remaining forests. Such link is twofold: on one side, faster transitions

[10]This result further aligns with findings from Dosi et al. (2020), demonstrating that employing more refined behavioral rules can be counterproductive in a world characterized by deep uncertainty.

[11]Analogous results are obtained when varying the number of periods after which firms are allowed to switch (q). As shown in Figure C.1, smaller values of q - just like high values of τ) - are associated with lower transition probabilities. On the other hand, modifying the parameter governing the amount of periods considered when evaluating the relative performance of sustainable and conventional farming (the memory parameter m) yields interesting results. When agents have lower memory, we observe a higher probability of transition. In this perspective, a smaller value of m can be interpreted as a measure of openness to novelties: when agents do not give too much weight to performances recorded in the distant past, they are more prone to positively evaluate sustainable farming when it becomes more productive. Unlike other measures of bounded rationality, lowering m also makes transitions faster (Figure C.1).

Figure 7: Transition end date against final share of remaining forests and transition length, for different observational horizons d^s and attitudes to switch τ.

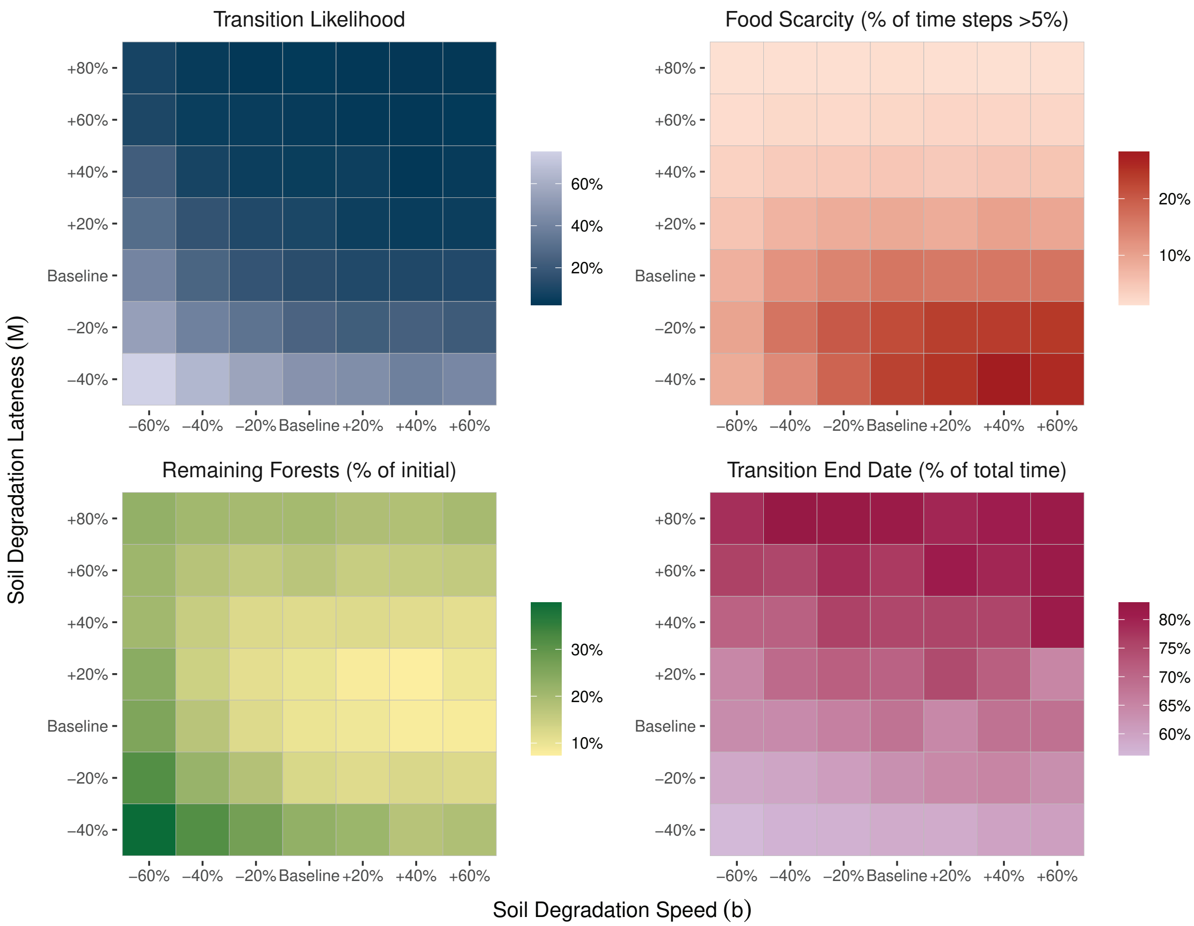


Note: Pooled runs for different values of d^s and τ (see Figure 6). Each dot is a single run. Straight lines are OLS best-fitting lines for grouped observations. Low Switching Intensity: $\tau \in \{-75\%, -50\%, -25\%, \text{Baseline}\}$; High Switching Intensity: $\tau \in \{+25\%, +50\%, +75\%\}$; all d^s. Small Ray of Observation: $d^s \in \{1, 2 \text{ (Baseline)}, 3\}$, High Ray of Observation: $d^s \in \{4, 5, 6\}$; all τ. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, expressed as percentage of simulation length. Length is defined as the difference between start and end date, expressed as percentage of simulation length. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry.

helps preserving the stock of forestry; on the other side, higher levels of deforestation imply a higher number of conventional farms in areas which, being virgin ones, will suffer soil degradation later in time, further masking signals of soil depletion and delaying - if not preventing at all - transition. Worryingly, late transition are also typically slower - right panel of Figure 7. This effect is not driven by a mechanical shift in the end date in slower transitions, as testified by the negative relationship between transition start date and its length - see Figure C.5. Such trade-off is particularly marked when the ray of observation is small and the attitude to switch is high, a combination which can lead to delays in efficient information processing.

The documented non-linear dynamics suggest that behavioral mechanisms play an important yet limited role. A conservative behavioral set-up appears to only marginally counterbalance the inclination to adopt short-run techniques that provide higher immediate gains, and this comes at the expense of slower transitions and subsequent increased forest exploitation. While extremely low values of both analyzed factors seem to suggest the presence of a positive tipping point, their efficacy is still constrained by the existence of a significant and persistent productivity gap between the two production techniques. This observation implies that policy interventions may be necessary to complement and enhance the effectiveness of behavioral changes in fostering sustainable transitions.

Figure 8: Heat-maps for different speeds of soil degradation b and values of soil degradation earliness M.



Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, averaged across runs which end up in a successful transition, expressed as percentage of simulation length. Food scarcity is given by the share of time steps with excess demand larger than 5%. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 500 Monte Carlo replications.

5.5 Environmental factors

Soil degradation is a complex phenomenon, affecting ecosystems throughout the planet. If its existence is ubiquitous, the speed at which it takes place is highly location specific (Mbow et al., 2017), and global figures are thus still a matter of discussion among soil scientists (Bindraban et al., 2012; Karstens et al., 2022). In this Section, we vary both the earliness and the speed of the soil degradation process, i.e. the starting point and the slope of the logistic curve - parameters M and b in Equation 2, respectively. This is conceptually equivalent to identifying different soil degradation scenarios along two dimensions: one in which soil degradation happens more or less early along with periods of conventional usage, and one in which it happens more or less gradually. Results are summarized in Figure 8.

The most striking result relates to the speed of soil degradation. Fast deterioration drastically reduce the likelihood of a transition towards a sustainable regime, regardless of the earliness. This indicates that bottom-up interactions between boundedly rational agents result in a lack of coordination, and the resulting aggregate performance deals very poorly with rapid changes. Accelerated soil degradation impedes the signal carried by lower output per worker (which is what firms actually observe) to timely spread in the lattice, leading to a higher chance of conventional lock-in. Inadequate responses to fast soil erosion in terms of raising awareness by farmers have been documented by empirical works (e.g., the study of Liang et al. (2010) on 3.4% increase in soil erosion in South China between 1950-1986).

Dynamics entailed by more probable lock-in scenarios are reflected by the evolution of food scarcity and remaining forestry: the higher the speed of soil degradation, the greater the increase in unsatisfied demand and the decrease in remaining forests. Only a very slow process of soil degradation allows agents to gradually collect the information needed to switch more actively to sustainable farming, partially limiting food scarcity and depletion of natural resources. Worryingly, faster soil depletion also leads to slower transitions. Very rapid changes in farm productivity are in fact likely to trigger, as a first reaction, a wave of acquisition, deforestation and hiring of additional workforce by conventional firms. These activities can temporarily mask the signs of soil depletion, lowering at the same time both the probability of transition and its speed. This is consistent with theories of regime shifts, which frequently emphasize how short-term costs of sustainable production techniques are typically high - as new technologies have not yet benefited from dynamic scale and learning effects - consequently shadowing their beneficial role in presence of rapid environmental changes (Kemp, 1994).

Analogous results are obtained when varying soil degradation lateness (M). By increasing the delay with which the damage due to soil degradation arises, transition probability monotonically decreases. As agents observe for a larger amount of period conventional farms performing better, they will tend to choose what they perceive as the most productive technique, as documented in Section 5.3. If the signal is delayed enough (+60% with respect to baseline), almost all simulations are pushed into a lock-in scenario. Food scarcity dynamics are quite intuitive, albeit not very informative. Indeed, the earlier the degradation process, the higher is the food scarcity, *ceteris paribus*: at the same point in time the amount of soil damage is in fact higher, hampering food production. The same holds true for transition date, which - everything else being equal - mechanically increase along with M. Finally, the stock of remaining forestry is certainly shaped by transition dynamics, explaining the higher stocks of forestry in early depletion scenarios. On the other hand, in more delayed scenarios the demand pressure on the system is, at each point in time, lower with respect earlier ones, thus explaining the non-monotonic results in the top part of the heat-map.

A joint analysis of both parameters reinforces these conclusions. Fast degradation is highly detrimental to transition probability, although for high values of M the probability of a lock-in is so high that the speed of the degradation process loses relevance. Finally, Figure C.3 confirms the negative trade-off between transition end date and remaining forestry, as well as the positive correlation between transition end date and speed - see also Figure C.6. Unlike those reported in Figure 7, the strengths of such relationships do not appear to change significantly along with b and M.

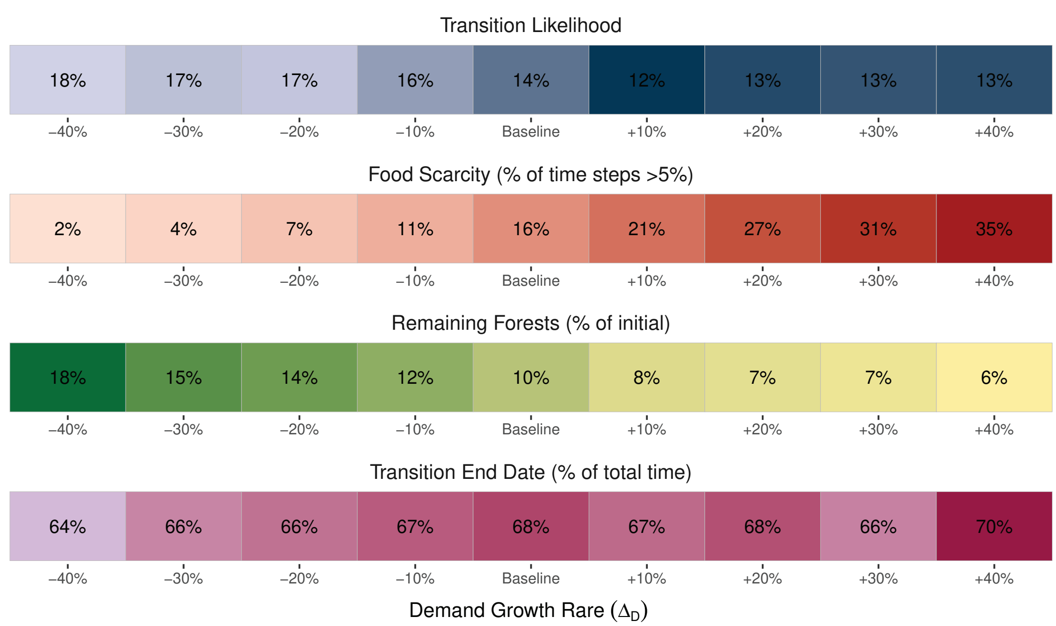
Overall, our experiments suggest the existence of negative tipping points highly correlated with the abruptness with which environmental damage manifest itself. This underscores both the need for anticipatory policies capable of realigning agents' short-run incentives with the long-run manifestation of environmental damages, and strongly suggests that the efficacy of interventions is highly time-dependent.

5.6 Demand pressure

Beside soil carrying capacity, food security is naturally related to another global constraint: demand growth (Leisinger et al., 2002; Brown, 1981). The projected increase in global population, along with that of standard of living, is embedded in the model through an exogenously increasing demand. We here experiment with different rates of growth of food demand. The effects of a varying demand pressure on transition dynamics are in principle ambiguous: lower demand helps sustainable farms gaining market shares when they outperform conventional farms working on already degraded soils, but it also implies higher market selection when conventional farms are still more productive.

As a matter of fact, the latter effect appears to dominate the former. Indeed, Figure 9 shows that a higher demand pressure leads to even lower chances of a sustainable transition: if on one hand the greater amount of food demanded leaves more room for sustainable survival, on the other hand it boosts conventional firms market shares, also encouraging deforestation and acquisition of defaulted farms. The decrease in transition likelihood appears to flatten out at very high levels of demand. The impact of higher demand pressure on food scarcity and the amount of forests is evidently negative, while the effect on transition end date is generally negative but less monotonic. Nonetheless, trade-offs between transition date, deforestation and transition length

Figure 9: Heat-maps for different rate of growth of food demand Δ_D.



Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, averaged across runs which end up in a successful transition, expressed as percentage of simulation length (white tiles represent configurations with no transitions registered). Food scarcity is given by the share of time steps with excess demand larger than 5%. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 500 Monte Carlo replications.

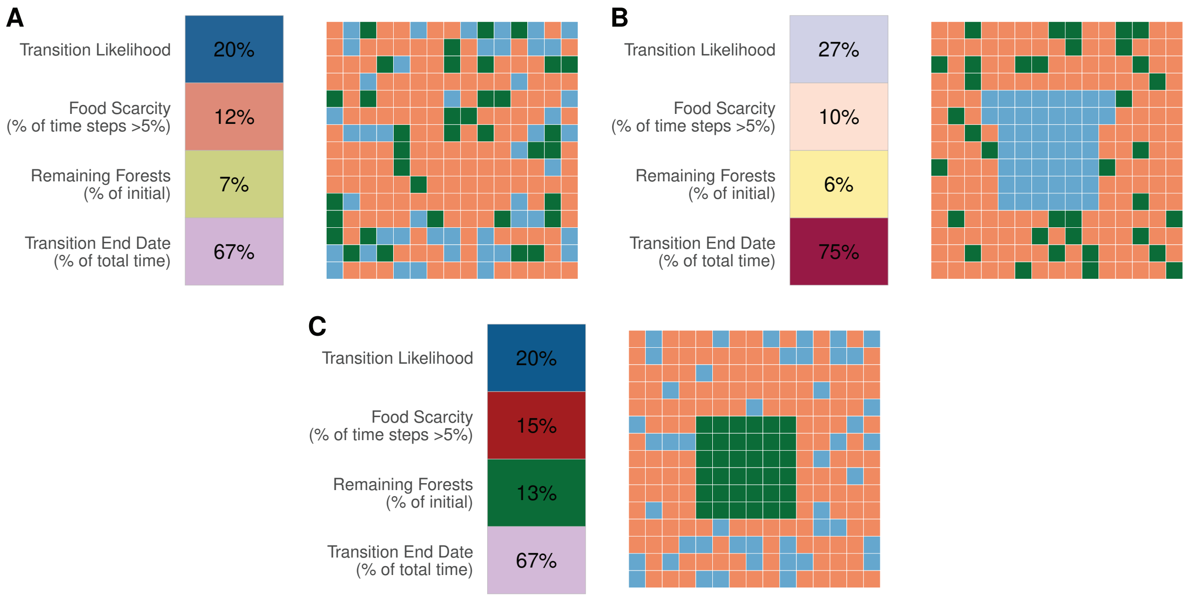
documented in Sections 5.4 and 5.5 are confirmed also within this experiment - see Figures C.4 and C.7. Taken together, these results underline the fundamental role of population growth in pressuring the agricultural/land-use sector. We underline that - in the current setup - food demand is strictly exogenous, while in the real world a persistent shortage of food (with consequent localized famines) will likely lead to negative feedbacks to productivity dynamics.

5.7 Spatial effects

In Sections 5.4 and 5.5 we explored transition dynamics under different behavioral rules and scenarios of soil degradation. In order to isolate their effect, the spatial distribution of forests and sustainable farms were kept fixed across scenarios. We now analyze separately the effects of different spatial setups. More precisely, we experiment with three prototypical initial spatial scenarios, depicted in Figure 10. These scenarios are highly idealized, and are designed in order to isolate the role of spatial configurations on modeled mechanisms of innovation and diffusion, and to study the emergence of lock-in dynamics which can be spatial dependent (Cecere et al., 2014). On one dimension, we vary the disposition of forestry: i) clustered at the center of the grid (Figures 10C, our baseline), or ii) randomly spread across the grid (Figures 10A and 10B). On the other dimension, we similarly change the location of sustainable farms: i) clustered at the center of the grid (Figure 10B) or ii) randomly spread across the grid (Figures 10A and 10C). The change in locations of forests and sustainable farms can provide valuable insights for sustainable policies, emphasizing the importance of tailoring them to the spatial specificities of the areas where they are implemented. Furthermore, they can be thought as stylizing alternative conservation policies - for example, policies which focus on preserving forests by promoting the presence of sustainable firms in proximity of forests, or that incentivize their clusterization so to favor mutual learning via imitation. In addition, they allow us to investigate the role of the interaction between spatial distribution of sustainable firms and forestry. To isolate these effect, we randomize initial productivities across Monte-Carlo simulations (see Figure 10 for details).

Clustering sustainable farms has, in principle, a twofold effect. On one hand, when farms using similar techniques are concentrated together, a 'community effect' arises: farms boost their productivity more easily by imitating each other, and are less likely to gather information on conventional farms performances - whose effects have been described in Section 5.4. The beneficial effect of sustainable clusterization has been documented in empirical works (see Bush et al. 2019 and Joffre et al. 2019 on reduced risk adoption and market skepticism) and in ABM models (e.g. Barbuto et al., 2019). On the other hand, more dispersed sustainable farms can trigger a 'diffusion effect': they will likely be more effective at spreading across the lattice when they become more productive, as more conventional firms would observe them not suffering any soil depletion. Trade-offs between advantages arising from clusterization and sparsity resemble closely the empirical cases of diffusion in homophily against heterophily environments (Rogers, 2010). On the other hand, forestry represents a finite common good, whose spatial disposition might favor or impede its over-exploitation. This, in turn, can in principle affect transition dynamics through a larger - or smaller - diffusion of over-exploitative agricultural regimes.

Figure 10: Heat-maps for different initial spatial scenarios.



Note: To isolate the effect, the number of each type of farm and the vector of initial productivities are maintained constant across Monte Carlo runs, while the spatial configuration of initial productivities is randomized across Monte Carlo. Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, averaged across runs which end up in a successful transition, expressed as percentage of simulation length. Food scarcity is given by the share of time steps with excess demand larger than 5%. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 500 Monte Carlo replications.

The effects of the distinct spatial configuration of agricultural regimes and forestry typically have a smaller magnitude with respect to those due to factors directly affecting technological adoption and dynamic learning - Sections 5.4 and 5.5. Nonetheless, they still reveal important patterns which complement those analyzed so far. By comparing Figures 10A and 10B, it is evident that the 'community effect' tends to dominate over the 'diffusion' one, at least in terms of transition likelihood. Clustering sustainable farms leads indeed to a higher probability of transition, driven by the positive productivity impact arising from imitation among neighboring farms. Nonetheless, such scenario results in a marginally lower share of remaining forests, as most of them are more easily exploitable by surrounding conventional farms. More relevantly, such scenario also leads to remarkably slower transitions. In other words, the gains obtained through imitation activities among spatially close farms spread more slowly across the lattice (via 'diffusion effect'). By comparing Figures 10A and 10C, it is instead visible the role of forestry sparsity. Clustering virgin lands intuitively results in a larger share of remaining forests: by being more spatially concentrated, such resources becomes naturally more difficult to exploit. Such 'induced' protection comes at the cost of a - marginally - higher food scarcity. Transition likelihood and end date are not affected.

6 Policy implications

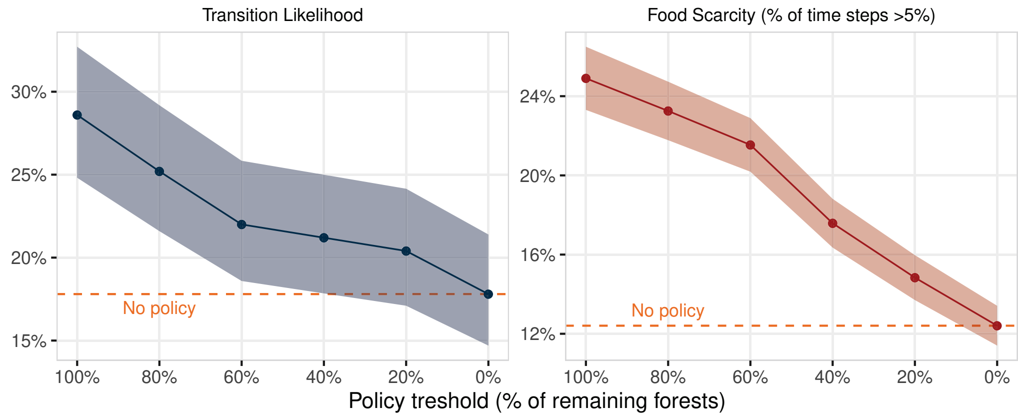
As illustrated in Section 5.3, the system exhibits limited capacity to facilitate a transition to a sustainable regime. This challenge becomes more pronounced in the presence of delayed or rapid environmental degradation, as discussed in Section 5.5. In Section 5.4, we showed how changes in agents behavior from the bottom-up can have relevant impacts, but overall insufficient in ensuring a rapid and probable transition. These results, taken together, underscore the need for policy interventions. In this section, leveraging the flexibility of AgriLOVE, we explore two distinct policies, both aimed at stimulating transition dynamics: one emulating a market-based approach, and one mimicking a command-and-control (regulation) strategy.

The role of deforestation as a *masking factor* has been extensively discussed in previous sections. Excessive exploitation of virgin land not only depletes limited environmental resources but also hinders a smooth transition to a sustainable regime. In previous simulations, the model setup did not incorporate any protection law for existing forests (Section 4.1.3). Firms willing to deforest were simply permitted to do so. Now, we analyze the effects of a policy prohibiting deforestation activities. Policies designed to achieve this objective have already been implemented in various regions, and their effectiveness has been confirmed by empirical studies (see, among others, Rudel et al., 2005; Angelsen, 2010). To simulate varying responsiveness among regulatory entities, which typically correlates with the severity of environmental exploitation, we implement the same policy after the remaining stock of forestry surpasses different thresholds. Given that the stock of forestry usually decreases monotonically, this approach also allows us to explore any time-dependent effectiveness of the policy.

As shown in Figure 11, prohibiting deforestation turns out to be quite effective in boosting transition likelihood, compared to the no policy scenario. Preventing the resort to deforestation hinders conventional firms from bolstering their market position during the early stages of the simulation, thereby dynamically improving the competitive standing of sustainable firms. The efficacy of the policy appears to be especially high when triggered early, i.e., when the stock of forest is still relatively abundant. However, it tends to diminish as the stock becomes relatively scarce. Conversely, prohibiting deforestation restricts the amount of land available for agricultural activities, resulting in an increased level of food scarcity proportionate to the percentage of the forestry stock preserved. Nonetheless, the emerging trade-off between the likelihood of successful transition and food scarcity becomes more pronounced when the policy is introduced later. This underscores the risks associated with delaying policy implementation.

While the impact of a regulatory policy on deforestation is significant, its effectiveness is, like other factors, capped by the productivity gap between conventional and sustainable techniques (Rudel et al., 2005). Therefore, we further investigate whether a market-based policy aimed at fostering sustainable innovation activities can significantly enhance the likelihood of transition. There is a small but growing body of evidence on the effectiveness to support experimentation and innovation for and by smallholder farmers (e.g. Wongtschowski et al., 2010; Ton et al., 2015). In line with this tradition, we allow sustainable farms to receive an additional

Figure 11: Transition likelihood and food scarcity under deforestation-prohibiting policy, triggered after different thresholds of remaining forests.



Note: To isolate the policy effect, the number of each type of farm and the vector of initial productivities are maintained constant across Monte Carlo runs,; spatial configuration of initial productivities, forests and sustainable farms positions are randomized across Monte Carlo. Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Food scarcity is given by the share of time steps with excess demand larger than 5% (Monte Carlo mean). Shaded areas represent 95% confidence intervals (Wilson-method binomial proportion confidence intervals for transition likelihood, Monte-Carlo confidence intervals for food scarcity). Orange dashed lines indicate values without policy (i.e. baseline model). 500 Monte Carlo replications.

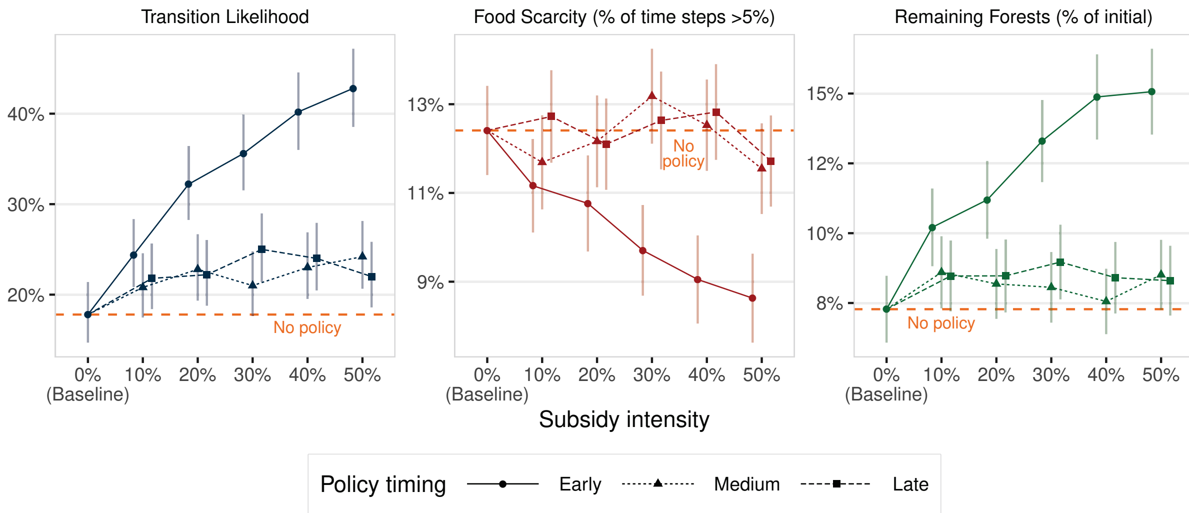
subsidy (or grant) targeted at innovation activities, with the amount being proportional to their innovation expenditures.

We experiment with varying degrees of subsidy intensity and three distinct timings of introduction (at the beginning of the simulation, at 25% and at 50% of the total simulation length).

As shown in Figure 12, early subsidizing of sustainable innovation is highly effective in enhancing the transition probability. Transition likelihood increases monotonically with subsidy intensity, albeit at a decreasing rate. In other words, subsidies can make an substantial difference, especially when they are large and explicitly targeted at closing the productivity gap. They are, however, destined to diminish in effectiveness progressively along with their abundance. Larger innovation expenditures can indeed facilitate searching and information activities, ensuring that sustainable farms successfully innovate. Nevertheless, the actual productivity gain will always be constrained by the size of the structural gap in growth potential compared to conventional farming. Because agents make decisions about adopting production techniques based on perceived productivity, relying solely on such market-based measures cannot guarantee full adoption of sustainable practices. Innovation subsidies can be highly effective in propelling the sustainable farming trajectory, but they cannot overcome the structural limits set by the inherent nature of the production technique itself. This emphasizes the need to couple market-based solutions with more command-and-control-oriented policies.

Remarkably, implementing a similar policy later in the simulation is found to be highly ineffective. Subsidies starting at 25% of the simulation length (as well as at 50%) have almost negligible impacts on transition likelihood, regardless of subsidy intensity. Correspondingly, they yield statistically insignificant results in terms of food scarcity and remaining forests. These results emphasize again the time-dependent significance of policy interventions, underscoring the presence of a rapidly closing window of opportunity.

Figure 12: Transition likelihood, food scarcity, and remaining forests under sustainable innovation subsidy policy, with varying intensity and triggered at different simulation points.



Note: To isolate the policy effect, the number of each type of farm and the vector of initial productivities are maintained constant across Monte Carlo runs,; spatial configuration of initial productivities, forests and sustainable farms positions are randomized across Monte Carlo. Policy timing: in the 'Early' scenario, policy starts after the transient (i.e. t=0); in the 'Medium' scenario, policy starts after at 25% of total simulation length (i.e. t=100); in the 'Late' scenario, policy starts after at 50% of total simulation length (i.e. t=200). Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Food scarcity and remaining forests are Monte Carlo means. Vertical lines represent 95% confidence intervals (Wilson-method binomial proportion confidence interval for transition likelihood, Monte-Carlo confidence interval for food scarcity and remaining forests). Vertical lines represent 95% confidence intervals (Wilson-method binomial proportion confidence intervals for transition likelihood, Monte-Carlo confidence intervals for food scarcity and remaining forests). Orange dashed lines indicate values without policy (i.e. baseline model). 500 Monte Carlo replications.

7 Conclusions and further research

In this work we extend the AgriLOVE model (Coronese et al., 2023) to investigate interactions between a conventional and a sustainable agro-technological regime in a smallholder farming economy exposed to explicit environmental boundaries. After showing the ability of the model to endogenously generate scenarios of successful transition, over-shooting and conventional lock-in, we study the ability of the system to favor a conversion to a sustainable regime. Our experiments allow us to identify critical leverage points to implement transition-enabling policies. We experiment with different behavioral, institutional and environmental factors to shape the likelihood, the velocity and the environmental impact of sustainable transition. We further test the implications of both command-and-control and market-based policies aimed at supporting sustainable transition.

Overall, our findings suggest a precarious and difficult pathway towards the adoption of sustainable agricultural practices at large scale. Though stylized, our scenarios pose serious concerns for future food security and forestry conservation. If on the one hand, we obtain that factors diminishing the productivity gap between conventional and sustainable techniques play a crucial role in fostering transition, on the other hand, we find that behavioral mechanisms, coupled with lack of foresight and without incentive-realigning policies, leads to a higher likelihood of conventional lock-ins. Remarkably, boundedly rational behaviours in the model do not come as a cost (Dosi et al., 2020); rather, they are typically associated with higher chances of transition, though they are relatively slow. We demonstrate how these concerns are exacerbated by growing population, whose demand pressure further penalizes sustainable agriculture. We document path dependency in the system and the existence of a significant relationship between the protection of "natural capital" (i.e., forests) and the likelihood of a conventional lock-in of the system, suggesting that timely policies fostering sustainable agriculture adoption and protecting natural resources can generate, via path dependence, relevant advantages, in line with recent studies (Martin et al., 2022). Indeed, we show that such path dependence enatils a non-negligible, non-trivial spatial component (Martin and Sunley, 2006). In line with recent studies reporting an increasing "ecological marginalization" of forest-dependent farmers Levers et al. (2021), our spatial experiments reinforce the idea that clustered, locally isolated communities of sustainable farmers are more likely to lead slowed transition dynamics, calling for global sustainable intensification strategies. These conclusions are aligned with recent works claiming the need to identify leverage points for policy interventions to transform land systems sustainably (Martin et al., 2022). Introducing two policies supporting sustainable agriculture in the model, we find that both in the case of command-and-control regulations and monetary subsidies time is of the essence, with policy effectiveness being tightly linked to an early period of implementation. These results are particularly timely in sight of the global farmers' protests against policies supporting sustainable farming, accused of generating higher prices and shrinking food production in the short-term. Indeed, bending to protests by farmers, governments from France to Sri Lanka are erasing bans on the use of agro-chemical products further delaying the implementation of transition-enabling policies.

The model generates testable land-change patterns, an exercise we plan to undertake in future works. Likewise, it is relatively straightforward to calibrate the model to specific areas of interest (e.g., the Amazon region). The current model can be further extended to account for more complex interactions, diffusion channels and environmental constraints, which are currently missing. For instance, future improvements of the model can include climate impacts, to explore the inter-plays between soil-degradation, climate-driven damages and the crucial role of carbon uptake played by forests and to mimic Representative Concentration Pathway (RCP) scenarios. Enriching agents' behaviors with different degrees of foresight, as well as different attitudes towards soil degradation and climate change (e.g., short-run vs long-run minded farmers, different adaptation strategies, as in Berger and Troost 2014) would further contribute to improve the model. Finally, introducing an endogenously determined food demand would generate non trivial dynamics worth exploring - via workforce availability and land productivity.

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Code and Data availability

Code and data used for this work are publicly available here.

References

Abrahamson, E. and Rosenkopf, L. (1997). Social network effects on the extent of innovation diffusion: A computer simulation. *Organization science*, 8(3):289–309.

Alene, A. D., Poonyth, D., and Hassan, R. M. (2000). Determinants of adoption and intensity of use of improved maize varieties in the central highlands of ethiopia: A tobit analysis. *Agrekon*, 39(4):633–643.

Allam, M., Radicetti, E., Quintarelli, V., Petroselli, V., Marinari, S., and Mancinelli, R. (2022). Influence of organic and mineral fertilizers on soil organic carbon and crop productivity under different tillage systems: A meta-analysis. *Agriculture*, 12(4):464.

Andriesse, J. (1977). *Nutrient level changes during a 20-year shifting cultivation cycle in Sarawak (Malaysia)*. Malaysian Society of Soil Science.

Angelsen, A. (2010). Policies for reduced deforestation and their impact on agricultural production. *Proceedings of the national Academy of Sciences*, 107(46):19639–19644.

Bacior, S. and Prus, B. (2018). Infrastructure development and its influence on agricultural land and regional sustainable development. *Ecological Informatics*, 44:82–93.

Balint, T., Lamperti, F., Mandel, A., Napoletano, M., Roventini, A., and Sapio, A. (2017a). Complexity and the economics of climate change: a survey and a look forward. *Ecological Economics*, 138:252–265.

Balint, T., Lamperti, F., Mandel, A., Napoletano, M., Roventini, A., and Sapio, A. (2017b). Complexity and the economics of climate change: a survey and a look forward. *Ecological Economics*, 138:252–265.

Bandiera, O. and Rasul, I. (2006). Social networks and technology adoption in northern mozambique. *The Economic Journal*, 116(514):869–902.

Barbier, E. B., Burgess, J. C., and Grainger, A. (2010). The forest transition: Towards a more comprehensive theoretical framework. *Land use policy*, 27(2):98–107.

Barbuto, A., Lopolito, A., and Santeramo, F. G. (2019). Improving diffusion in agriculture: an agent-based model to find the predictors for efficient early adopters. *Agricultural and food economics*, 7(1):1.

Barnaud, C., Promburom, T., Trébuil, G., and Bousquet, F. (2007). An evolving simulation/gaming process to facilitate adaptive watershed management in northern mountainous thailand. *Simulation & gaming*, 38(3):398–420.

Barrett, C. B., Christiaensen, L., Sheahan, M., and Shimeles, A. (2017). On the structural transformation of rural africa. *Journal of African Economies*, 26(suppl_1):i11–i35.

Bauters, M., Moonen, P., Summerauer, L., Doetterl, S., Wasner, D., Griepentrog, M., Mumbanza, F. M., Kearsley, E., Ewango, C., Boyemba, F., et al. (2021). Soil nutrient depletion and tree functional composition shift following repeated clearing in secondary forests of the congo basin. *Ecosystems*, 24(6):1422–1435.

Beard, R. and Purcell, T. (2000). Spatial replicator dynamics as a model of agricultural technology adoption. Technical report.

Beilin, R., Reichelt, N. T., King, B. J., Long, A., and Cam, S. (2013). Transition landscapes and social networks: examining on-gound community resilience and its implications for policy settings in multiscalar systems. *Ecology and Society*, 18(2).

Belton, B., Win, M. T., Zhang, X., and Filipski, M. (2021). The rapid rise of agricultural mechanization in myanmar. *Food Policy*, 101:102095.

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural economics*, 25(2-3):245–260.

Berger, T., Schreinemachers, P., and Woelcke, J. (2006). Multi-agent simulation for the targeting of development policies in less-favored areas. *Agricultural Systems*, 88(1):28–43.

Berger, T. and Troost, C. (2012). Agent-based modelling in the agricultural economics tradition of recursive farm modelling and adaptive micro-systems.

Berger, T. and Troost, C. (2014). Agent-based modelling of climate adaptation and mitigation options in agriculture. *Journal of Agricultural Economics*, 65(2):323–348.

Bert, F. E., Podestá, G. P., Rovere, S. L., Menéndez, Á. N., North, M., Tatara, E., Laciana, C. E., Weber, E., and Toranzo, F. R. (2011). An agent based model to simulate structural and land use changes in agricultural systems of the argentine pampas. *Ecological Modelling*, 222(19):3486–3499.

Bindraban, P. S., van der Velde, M., Ye, L., Van den Berg, M., Materechera, S., Kiba, D. I., Tamene, L., Ragnarsdóttir, K. V., Jongschaap, R., Hoogmoed, M., et al. (2012). Assessing the impact of soil degradation on food production. *Current Opinion in Environmental Sustainability*, 4(5):478–488.

Biswas, C. and Benbi, D. (1996). Sustainable yield trends of irrigated maize and wheat in a long-term experiment on a loamy sand in semi-arid india. *Nutrient Cycling in Agroecosystems*, 46(3):225–234.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, 99(suppl_3):7280–7287.

Borrelli, P., Lugato, E., Montanarella, L., and Panagos, P. (2017). A new assessment of soil loss due to wind erosion in european agricultural soils using a quantitative spatially distributed modelling approach. *Land degradation & development*, 28(1):335–344.

Bousquet, F. and Le Page, C. (2004). Multi-agent simulations and ecosystem management: a review. *Ecological modelling*, 176(3-4):313–332.

Brenner, T. (2006). Agent learning representation: advice on modelling economic learning. *Handbook of computational economics*, 2:895–947.

Brock, W. A. and Hommes, C. H. (1997). A rational route to randomness. *Econometrica: Journal of the Econometric Society*, pages 1059–1095.

Brown, L. R. (1981). World population growth, soil erosion, and food security. *Science*, pages 995–1002.

Brown, L. R. and Wolf, E. C. (1984). Soil erosion: Quiet crisis in the world economy. worldwatch paper 60.

Bush, S. R., Oosterveer, P., Bottema, M., Meuwissen, M., de Mey, Y., Chamsai, S., Lien, H. H., and Chadag, M. (2019). Inclusive environmental performance through 'beyond-farm'aquaculture governance. *Current Opinion in Environmental Sustainability*, 41:49–55.

Cecere, G., Corrocher, N., Gossart, C., and Ozman, M. (2014). Lock-in and path dependence: an evolutionary approach to eco-innovations. *Journal of Evolutionary Economics*, 24(5):1037–1065.

Chapin III, F. S., Carpenter, S. R., Kofinas, G. P., Folke, C., Abel, N., Clark, W. C., Olsson, P., Smith, D. M. S., Walker, B., Young, O. R., et al. (2010). Ecosystem stewardship: sustainability strategies for a rapidly changing planet. *Trends in ecology & evolution*, 25(4):241–249.

Chattoe, E. and Gilbert, N. (1998). Modelling the adoption of agri-environmental measures using decision plan nets. In *IMAGES Meeting, Clermont-Ferrand (M3)*, pages 25–29.

Chiaromonte, F. and Dosi, G. (1993). Heterogeneity, competition, and macroeconomic dynamics. *Structural Change and Economic Dynamics*, 4(1):39–63.

Commission, J. F. C. A. and Organization, W. H. (2007). *Organically produced foods*. Food & Agriculture Org.

Conforti, P. (2017). Looking ahead in world food and agriculture: perspectives to 2050. food and agriculture organization of the united nations (fao).

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in ghana. *American economic review*, 100(1):35–69.

Cook, P. and Cook, C. (1990). Methodological review of analyses of rural transportation impacts in developing countries. *Transportation Research Record*, 1274:167–78.

Coomes, O. T., Barham, B. L., MacDonald, G. K., Ramankutty, N., and Chavas, J.-P. (2019). Leveraging total factor productivity growth for sustainable and resilient farming. *Nature Sustainability*, 2(1):22–28.

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., and Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences*, 116(43):21450–21455.

Coronese, M., Occelli, M., Lamperti, F., and Roventini, A. (2023). Agrilove: agriculture, land-use and technical change in an evolutionary, agent-based model. *Ecological Economics*, 208:107756.

Courdier, R., Guerrin, F., Andriamasinoro, F. H., and Paillat, J.-M. (2002). Agent-based simulation of complex systems: application to collective management of animal wastes. *Journal of Artificial Societies and Social Simulation*, 5(3).

Dabbert, S. and Madden, P. (1986). The transition to organic agriculture: A multi-year simulation model of a pennsylvania farm. *American Journal of Alternative Agriculture*, 1(3):99–107.

Daily, G. C. (2013). Nature's services: societal dependence on natural ecosystems (1997). In *The Future of Nature*, pages 454–464. Yale University Press.

Darnhofer, I., Bellon, S., Dedieu, B., and Milestad, R. (2010). Adaptiveness to enhance the sustainability of farming systems. a review. *Agronomy for sustainable development*, 30(3):545–555.

de la Cruz, V. Y. V., Cheng, W., Tawaraya, K., et al. (2023). Yield gap between organic and conventional farming systems across climate types and sub-types: A meta-analysis. *Agricultural Systems*, 211:103732.

Deffuant, G., Huet, S., Bousset, J., Henriot, J., Amon, G., Weisbuch, G., et al. (2002). Agent based simulation of organic farming conversion in allier département. *Complexity and Ecosystem Management*, pages 158–189.

Delgado, C., Rosegrant, M., Steinfeld, H., Ehui, S., and Courbois, C. (2001). Livestock to 2020: The next food revolution. *Outlook on Agriculture*, 30(1):27–29.

Demiryurek, K., Erdem, H., Ceyhan, V., Atasever, S., and Uysal, O. (2008). Agricultural information systems and communication networks: the case of dairy farmers in samsun province of turkey. *Information research*, 13(2):13–2.

Diao, X., Agandin, J., Fang, P., Justice, S. E., Kufoalor, D. S., and Takeshima, H. (2018). *Agricultural mechanization in Ghana: Insights from a recent field study*, volume 1729. Intl Food Policy Res Inst.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of economic literature*, pages 1120–1171.

Dosi, G., Fagiolo, G., and Roventini, A. (2010). Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. *Journal of Economic Dynamics and Control*, 34(9):1748–1767.

Dosi, G., Freeman, C., Nelson, R., Silverberg, G., and Soete, L. (1988). Technical change and economic theory. Technical report, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced ....

Dosi, G., Marsili, O., Orsenigo, L., and Salvatore, R. (1995). Learning, market selection and the evolution of industrial structures. *Small Business Economics*, 7(6):411–436.

Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J. E., and Treibich, T. (2020). Rational heuristics? expectations and behaviors in evolving economies with heterogeneous interacting agents. *Economic Inquiry*, 58(3):1487–1516.

Dosi, G. and Nelson, R. R. (2010). Technical change and industrial dynamics as evolutionary processes. *Handbook of the Economics of Innovation*, 1:51–127.

Dosi, G. and Roventini, A. (2019). More is different... and complex! the case for agent-based macroeconomics. *Journal of Evolutionary Economics*, 29:1–37.

Emerick, K., de Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6):1537–61.

Fagiolo, G. and Dosi, G. (2003). Exploitation, exploration and innovation in a model of endogenous growth with locally interacting agents. *Structural Change and Economic Dynamics*, 14(3):237–273.

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A., and Roventini, A. (2019). Validation of agent-based models in economics and finance. In *Computer Simulation Validation*, pages 763–787. Springer.

Fagiolo, G. and Roventini, A. (2017). Macroeconomic policy in dsge and agent-based models redux: New developments and challenges ahead. *Journal of Artificial Societies and Social Simulation*, 20(1).

FAO. (2013). *FAO Statistical Yearbook: World Food and Agriculture*. FAO.

Farmer, J. D. and Foley, D. (2009). The economy needs agent-based modelling. *Nature*, 460(7256):685–686.

Farmer, J. D., Hepburn, C., Ives, M. C., Hale, T., Wetzer, T., Mealy, P., Rafaty, R., Srivastav, S., and Way, R. (2019). Sensitive intervention points in the post-carbon transition. *Science*, 364(6436):132–134.

Fatichi, S., Or, D., Walko, R., Vereecken, H., Young, M. H., Ghezzehei, T. A., Hengl, T., Kollet, S., Agam, N., and Avissar, R. (2020). Soil structure is an important omission in earth system models. *Nature Communications*, 11(1):1–11.

Ferng, J.-J. (2005). Local sustainable yield and embodied resources in ecological footprint analysis—a case study on the required paddy field in taiwan. *Ecological Economics*, 53(3):415–430.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., et al. (2011). Solutions for a cultivated planet. *Nature*, 478(7369):337.

Foxon, T. J. (2011). A coevolutionary framework for analysing a transition to a sustainable low carbon economy. *Ecological economics*, 70(12):2258–2267.

Freeman, C. (1996). The greening of technology and models of innovation. *Technological forecasting and social change*, 53(1):27–39.

Gabriel, D., Sait, S. M., Kunin, W. E., and Benton, T. G. (2013). Food production vs. biodiversity: comparing organic and conventional agriculture. *Journal of applied ecology*, 50(2):355–364.

Gebrehiwot, A. A., Hashemi-Beni, L., Kurkalova, L. A., Liang, C. L., and Jha, M. K. (2022). Using abm to study the potential of land use change for mitigation of food deserts. *Sustainability*, 14(15):9715.

Gellrich, M., Baur, P., Koch, B., and Zimmermann, N. E. (2007). Agricultural land abandonment and natural forest re-growth in the swiss mountains: a spatially explicit economic analysis. *Agriculture, Ecosystems & Environment*, 118(1-4):93–108.

Gomiero, T., Pimentel, D., and Paoletti, M. G. (2011). Environmental impact of different agricultural management practices: conventional vs. organic agriculture. *Critical reviews in plant sciences*, 30(1-2):95–124.

Grassini, P., Eskridge, K. M., and Cassman, K. G. (2013). Distinguishing between yield advances and yield plateaus in historical crop production trends. *Nature communications*, 4:2918.

Grau, H. R., Gasparri, N. I., and Aide, T. M. (2005). Agriculture expansion and deforestation in seasonally dry forests of north-west argentina. *Environmental Conservation*, 32(2):140–148.

Haddaway, N. R., Styles, D., and Pullin, A. S. (2014). Evidence on the environmental impacts of farm land abandonment in high altitude/mountain regions: a systematic map. *Environmental Evidence*, 3(1):17.

Happe, K., Kellermann, K., and Balmann, A. (2006). Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator agripolis, its adaptation and behavior. *Ecology and Society*, 11(1).

Hötte, K. (2019). Skill transferability and the stability of transition pathways-a learning-based explanation for patterns of diffusion.

Huntley, E., Collins, E., and Swisher, M. (2013). Effects of organic and conventional farm practices on soil quality. *University of Florida*.

IFOAM (2012). The ifoam norms for organic production and processing.

Janssen, M. A. (2007). Coordination in irrigation systems: an analysis of the lansing–kremer model of bali. *Agricultural Systems*, 93(1-3):170–190.

Janssen, M. A. and Ostrom, E. (2006). Governing social-ecological systems. *Handbook of computational economics*, 2:1465–1509.

Joffre, O. M., Poortvliet, P. M., and Klerkx, L. (2019). To cluster or not to cluster farmers? influences on network interactions, risk perceptions, and adoption of aquaculture practices. *Agricultural systems*, 173:151–160.

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., et al. (2017). Brief history of agricultural systems modeling. *Agricultural systems*, 155:240–254.

Kamau, H., Roman, S., and Biber-Freudenberger, L. (2023). Nearly half of the world is suitable for diversified farming for sustainable intensification. *Communications Earth & Environment*, 4(1):446.

Karstens, K., Bodirsky, B. L., Dietrich, J. P., Dondini, M., Heinke, J., Kuhnert, M., Müller, C., Rolinski, S., Smith, P., Weindl, I., et al. (2022). Management-induced changes in soil organic carbon on global croplands. *Biogeosciences*, 19(21):5125–5149.

Kaufmann, P., Stagl, S., and Franks, D. W. (2009). Simulating the diffusion of organic farming practices in two new eu member states. *Ecological Economics*, 68(10):2580–2593.

Kaye-Blake, W. H., Li, F. Y., Martin, A., McDermott, A., Rains, S. T., Sinclair, S., and Kira, A. (2010). Multi-agent simulation models in agriculture: a review of their construction and uses.

Kemp, R. (1994). Technology and the transition to environmental sustainability: the problem of technological regime shifts. *Futures*, 26(10):1023–1046.

Kendall, H. W. and Pimentel, D. (1994). Constraints on the expansion of the global food supply. *Ambio*, pages 198–205.

Kephe, P. N., Siewe, L. C., Lekalakala, R. G., Kwabena Ayisi, K., and Petja, B. M. (2022). Optimizing smallholder farmers' productivity through crop selection, targeting and prioritization framework in the limpopo and free state provinces, south africa. *Frontiers in Sustainable Food Systems*, page 76.

Kopittke, P. M., Menzies, N. W., Wang, P., McKenna, B. A., and Lombi, E. (2019). Soil and the intensification of agriculture for global food security. *Environment international*, 132:105078.

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *science*, 304(5677):1623–1627.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., and Sapio, A. (2018). Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. *Ecological Economics*, 150:315–339.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., and Sapio, A. (2020). Climate change and green transitions in an agent-based integrated assessment model. *Technological Forecasting and Social Change*, 153:119806.

Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., and Khorenzhenko, I. (2019). Towards agent-based integrated assessment models: examples, challenges, and future developments. *Regional environmental change*, 19(3):747–762.

Leisinger, K. M., Schmitt, K., and Pandya-Lorch, R. (2002). Six billion and counting: population growth and food security in the 21st century. Technical report.

Lenton, T., Armstrong McKay, D., Loriani, S., Abrams, J., Lade, S., Donges, J. F., Milkoreit, M., Powell, T., Smith, S., Zimm, C., et al. (2023). The global tipping points report 2023.

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., and Schellnhuber, H. J. (2008). Tipping elements in the earth's climate system. *Proceedings of the national Academy of Sciences*, 105(6):1786–1793.

Levers, C., Romero-Muñoz, A., Baumann, M., De Marzo, T., Fernández, P. D., Gasparri, N. I., Gavier-Pizarro, G. I., de Waroux, Y. l. P., Piquer-Rodríguez, M., Semper-Pascual, A., et al. (2021). Agricultural expansion and the ecological marginalization of forest-dependent people. *Proceedings of the National Academy of Sciences*, 118(44).

LI, C.-x., Yun, S., ZHANG, L.-l., et al. (2018). Effects of long-term organic fertilization on soil microbiologic characteristics, yield and sustainable production of winter wheat. *Journal of integrative agriculture*, 17(1):210–219.

Li, F. G., Trutnevyte, E., and Strachan, N. (2015). A review of socio-technical energy transition (stet) models. *Technological Forecasting and Social Change*, 100:290–305.

Liang, Y., Li, D., Lu, X., Yang, X., Pan, X., Mu, H., Shi, D., and Zhang, B. (2010). Soil erosion changes over the past five decades in the red soil region of southern china. *Journal of Mountain Science*, 7(1):92–99.

Loorbach, D., Avelino, F., Haxeltine, A., Wittmayer, J. M., O'Riordan, T., Weaver, P., and Kemp, R. (2016). The economic crisis as a game changer? exploring the role of social construction in sustainability transitions. *Ecology and Society*, 21(4).

MacDonald, J. M., Hoppe, R. A., and Newton, D. (2018). Three decades of consolidation in us agriculture. Technical report, USDA.

MacLeod, A., Baker, R., Cannon, R., et al. (2005). Costs and benefits of european community (ec) measures against an invasive alien species: current and future impacts of diabrotica virgifera virgifera in england & wales. In *A paper prepared for symposium on Introduction and Spread of Invasive Species*, pages 9–11.

Manson, S. M., Jordan, N. R., Nelson, K. C., and Brummel, R. F. (2016). Modeling the effect of social networks on adoption of multifunctional agriculture. *Environmental modelling & software*, 75:388–401.

Marchand, S. (2012). The relationship between technical efficiency in agriculture and deforestation in the brazilian amazon. *Ecological Economics*, 77:166–175.

Markard, J., Raven, R., and Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. *Research policy*, 41(6):955–967.

Martin, D. A., Andrianisaina, F., Fulgence, T. R., Osen, K., Rakotomalala, A. A. N. A., Raveloaritiana, E., Soazafy, M. R., Wurz, A., Andriafanomezantsoa, R., Andriamaniraka, H., Andrianarimisa, A., Barkmann, J., Dröge, S., Grass, I., Guerrero-Ramirez, N., Hänke, H., Hölscher, D., Rakouth, B., Ranarijaona, H. L. T., Randriamanantena, R., Ratsoavina, F. M., Ravaomanarivo, L. H. R., Schwab, D., Tscharntke, T., Zemp, D. C., and Kreft, H. (2022). Land-use trajectories for sustainable land system transformations: Identifying leverage points in a global biodiversity hotspot. *Proceedings of the National Academy of Sciences*, 119(7).

Martin, R. and Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of economic geography*, 6(4):395–437.

Martini, E. A., Buyer, J. S., Bryant, D. C., Hartz, T. K., and Denison, R. F. (2004). Yield increases during the organic transition: improving soil quality or increasing experience? *Field Crops Research*, 86(2-3):255–266.

Marvuglia, A., Bayram, A., Baustert, P., Gutiérrez, T. N., and Igos, E. (2022). Agent-based modelling to simulate farmers' sustainable decisions: Farmers' interaction and resulting green consciousness evolution. *Journal of Cleaner Production*, 332:129847.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., and Gotts, N. M. (2007). Agent-based land-use models: a review of applications. *Landscape Ecology*, 22(10):1447–1459.

Mazzoncini, M., Canali, S., Giovannetti, M., Castagnoli, M., Tittarelli, F., Antichi, D., Nannelli, R., Cristani, C., and Bàrberi, P. (2010). Comparison of organic and conventional stockless arable systems: a multidisciplinary approach to soil quality evaluation. *Applied soil ecology*, 44(2):124–132.

Mbow, H.-O. P., Reisinger, A., Canadell, J., and O'Brien, P. (2017). Special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems (sr2). *Ginevra, IPCC*.

McCann, J. C. (1995). *People of the plow: an agricultural history of Ethiopia, 1800–1990*. Univ of Wisconsin Press.

McKenzie, F. C. and Williams, J. (2015). Sustainable food production: constraints, challenges and choices by 2050. *Food Security*, 7(2):221–233.

Meadows, D. and Randers, J. (2012). *The limits to growth: the 30-year update*. Routledge.

Meadows, D. H., Meadows, D. L., Randers, J., and Behrens, W. W. (1972). The limits to growth. *New York*, 102:27.

Meng, N. and Zhou, J. (2022). Evolutionary game analysis of farmers' conservation tillage behavior in black soil areas guided by deep learning. *Computational Intelligence and Neuroscience*, 2022.

Moser, P. (2020). *Economics of Research and Innovation in Agriculture*. University of Chicago Press.

Moss, S., Downing, T., and Rouchier, J. (2000). Demonstrating the role of stakeholder participation: An agent based social simulation model of water demand policy and response. *CPM Report No. 00-76, Centre for Policy Modelling, The Business School, Manchester Metropolitan University, Manchester, UK*, 29:39.

Mrema, G., Soni, P., Rolle, R., et al. (2014). A regional strategy for sustainable agricultural mechanization: sustainable mechanization across agri-food chains in asia and the pacific region. *RAP Publication*, 24(2014).

Mueller, B. and Chan, M.-K. (2015). Wage labor, agriculture-based economies, and pathways out of poverty: taking stock of the evidence. Technical report.

Nelson, R. R. (2016). The sciences are different and the differences matter. *Research Policy*, 45(9):1692–1701.

Nelson, R. R. and Winter, S. G. (1973). Toward an evolutionary theory of economic capabilities. *The American Economic Review*, 63(2):440–449.

Nelson, R. R. and Winter, S. G. (1982). Winter. 1982. *An evolutionary theory of economic change*, pages 929–964.

Niamir, L., Filatova, T., Voinov, A., and Bressers, H. (2018). Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. *Energy policy*, 118:325–345.

Nieddu, M., Bertani, F., and Ponta, L. (2021). The sustainability transition and the digital transformation: two challenges for agent-based macroeconomic models. *Review of Evolutionary Political Economy*, pages 1–34.

Noel, S. (2015). Economics of land degradation initiative: Report for policy and decision makers_ reaping economic and environmental benefits from sustainable land management. *Bonn, Germany: ELD Initiative and Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH.*

Nye, P. H. and Greenland, D. J. (1965). *The soil under shifting cultivation*. Bucks, Eng.

Olabisi, L., Wang, R., and Ligmann-Zielinska, A. (2015). Why don't more farmers go organic? using a stakeholder-informed exploratory agent-based model to represent the dynamics of farming practices in the philippines. *Land*, 4(4):979–1002.

Oldeman, L., Hakkeling, R., and Sombroek, W. G. (2017). World map of the status of human-induced soil degradation: an explanatory note.

Palagi, E., Coronese, M., Lamperti, F., and Roventini, A. (2022). Climate change and the nonlinear impact of precipitation anomalies on income inequality. *Proceedings of the National Academy of Sciences*, 119(43):e2203595119.

Pang, X. and Letey, J. (2000). Organic farming challenge of timing nitrogen availability to crop nitrogen requirements. *Soil Science Society of America Journal*, 64(1):247–253.

Pant, L. P. and Hambly-Odame, H. (2009). Innovations systems in renewable natural resource management and sustainable agriculture: a literature review. *African Journal of Science, Technology, Innovation and Development*, 1(1):103–135.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., and Deadman, P. (2003). Multi-agent systems for the simulation of land-use and land-cover change: a review. *Annals of the association of American Geographers*, 93(2):314–337.

Peters, B., Herens, M., and Brouwers, J. (2018). Capturing social innovations in agricultural transformation from the field: Outcomes of a write-shop. *Sustainability*, 10(12):4727.

Pimentel, D. and Giampietro, M. (1994). Global population, food and the environment. *Trends in ecology & evolution*, 9(6):239.

Pomp, M. and Burger, K. (1995). Innovation and imitation: Adoption of cocoa by indonesian smallholders. *World Development*, 23(3):423–431.

Ponisio, L. C., M'Gonigle, L. K., Mace, K. C., Palomino, J., de Valpine, P., and Kremen, C. (2015). Diversification practices reduce organic to conventional yield gap. *Proceedings of the Royal Society B: Biological Sciences*, 282(1799):20141396.

Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, 362(6417):eaav0294.

Prus, P. and Sikora, M. (2021). The impact of transport infrastructure on the sustainable development of the region,Äîcase study. *Agriculture*, 11(4).

Ramankutty, N., Mehrabi, Z., Waha, K., Jarvis, L., Kremen, C., Herrero, M., and Rieseberg, L. H. (2018). Trends in global agricultural land use: implications for environmental health and food security. *Annual review of plant biology*, 69:789–815.

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., and Foley, J. A. (2012). Recent patterns of crop yield growth and stagnation. *Nature communications*, 3:1293.

Razanakoto, O., Razafindraibe, R., Andriamananjara, A., Razafimanantsoa, M.-P., Rakotoson, T., Smolders, E., and Rabeharisoa, L. (2018). Failures in agricultural innovation due to poor understanding of farmers' predispositions. *Development in Practice*, 28(5):691–704.

Roberts, S., Vilakazi, T., and Simbanegavi, W. (2017). *Competition, regional integration and inclusive growth in Africa: A research agenda*. Wits University Press.

Robertson, G., Gross, K., and Hamilton, S. (2014). Farming for ecosystem services: An ecological approach to production agriculture bioscience. 64 (5).

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin III, F. S., Lambin, E., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., et al. (2009). Planetary boundaries: exploring the safe operating space for humanity. *Ecology and society*, 14(2).

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., et al. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio*, 46(1):4–17.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Roling, N. (1988). *Extension science: Information systems in agricultural development*. CUP Archive.

Roser, M., Ritchie, H., and Ortiz-Ospina, E. (2013). World population growth. *Our World in Data*.

Rudel, T. K., Coomes, O. T., Moran, E., Achard, F., Angelsen, A., Xu, J., and Lambin, E. (2005). Forest transitions: towards a global understanding of land use change. *Global environmental change*, 15(1):23–31.

Saifi, B. and Drake, L. (2008). A coevolutionary model for promoting agricultural sustainability. *Ecological Economics*, 65(1):24–34.

Sanchez, P. A., Shepherd, K. D., Soule, M. J., Place, F. M., Buresh, R. J., Izac, A.-M. N., Mokwunye, A. U., Kwesiga, F. R., Ndiritu, C. G., and Woomer, P. L. (1997). Soil fertility replenishment in africa: an investment in natural resource capital. *Replenishing soil fertility in Africa*, (replenishingsoi):1–46.

Scherr, S. J. (1999). *Soil degradation: a threat to developing-country food security by 2020?*, volume 27. Intl Food Policy Res Inst.

Schmit, C. and Rounsevell, M. (2006). Are agricultural land use patterns influenced by farmer imitation? *Agriculture, ecosystems & environment*, 115(1-4):113–127.

Schrama, M., De Haan, J., Kroonen, M., Verstegen, H., and Van der Putten, W. (2018). Crop yield gap and stability in organic and conventional farming systems. *Agriculture, ecosystems & environment*, 256:123–130.

Schreinemachers, P. and Berger, T. (2011). An agent-based simulation model of human–environment interactions in agricultural systems. *Environmental Modelling & Software*, 26(7):845–859.

Scialabba, N. E.-H. and Müller-Lindenlauf, M. (2010). Organic agriculture and climate change. *Renewable agriculture and food systems*, 25(2):158–169.

Shennan, C., Krupnik, T. J., Baird, G., Cohen, H., Forbush, K., Lovell, R. J., and Olimpi, E. M. (2017). Organic and conventional agriculture: a useful framing? *Annual Review of Environment and Resources*, 42:317–346.

Silverberg, G. (1991). Adoption and diffusion of technology as a collective evolutionary process. In *Diffusion of technologies and social behavior*, pages 209–229. Springer.

Silverberg, G., Dosi, G., and Orsenigo, L. (1988). Innovation, diversity and diffusion: a self-organisation model. *The Economic Journal*, 98(393):1032–1054.

Sims, B. and Kienzle, J. (2017). Sustainable agricultural mechanization for smallholders: what is it and how can we implement it? *Agriculture*, 7(6):50.

Sivramkrishna, S. and Jyotishi, A. (2008). Monopsonistic exploitation in contract farming: articulating a strategy for grower cooperation. *Journal of International Development: The Journal of the Development Studies Association*, 20(3):280–296.

Smith, L. G., Kirk, G. J., Jones, P. J., and Williams, A. G. (2019). The greenhouse gas impacts of converting food production in england and wales to organic methods. *Nature communications*, 10(1):4641.

Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., and Ludwig, C. (2015a). The trajectory of the anthropocene: the great acceleration. *The Anthropocene Review*, 2(1):81–98.

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W., De Wit, C. A., et al. (2015b). Planetary boundaries: Guiding human development on a changing planet. *Science*, 347(6223):1259855.

Swinnen, J. F. (2007). The dynamics of vertical coordination in agri-food supply chains in transition countries. *2007), Global Supply Chains, Standards and the Poor, CABI, Oxon*, pages 42–58.

Tàbara, J. D., Frantzeskaki, N., Hölscher, K., Pedde, S., Kok, K., Lamperti, F., Christensen, J. H., Jäger, J., and Berry, P. (2018). Positive tipping points in a rapidly warming world. *Current Opinion in Environmental Sustainability*, 31:120–129.

Tachibana, T., Nguyen, T. M., and Otsuka, K. (2001). Agricultural intensification versus extensification: a case study of deforestation in the northern-hill region of vietnam. *Journal of Environmental Economics and Management*, 41(1):44–69.

Thacker, S., Adshead, D., Fay, M., Hallegatte, S., Harvey, M., Meller, H., O'Regan, N., Rozenberg, J., Watkins, G., and Hall, J. W. (2019). Infrastructure for sustainable development. *Nature Sustainability*, 2(4):324–331.

Thebaud, O., Locatelli, B., et al. (2001). Modelling the emergence of resource-sharing conventions: an agent-based approach. *Journal of Artificial Societies and Social Simulation*, 4(2):3.

Thierfelder, C. and Wall, P. C. (2011). Reducing the risk of crop failure for smallholder farmers in africa through the adoption of conservation agriculture. In *Innovations as key to the green revolution in Africa*, pages 1269–1277. Springer.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., and Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, 418(6898):671–677.

Tilman, D., Fargione, J., Wolff, B., D'antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W. H., Simberloff, D., and Swackhamer, D. (2001). Forecasting agriculturally driven global environmental change. *science*, 292(5515):281–284.

Tinker, P. B., Ingram, J. S., and Struwe, S. (1996). Effects of slash-and-burn agriculture and deforestation on climate change. *Agriculture, Ecosystems & Environment*, 58(1):13–22.

Tirkaso, W. and Hailu, A. (2022). Does neighborhood matter? spatial proximity and farmers' technical efficiency. *Agricultural Economics*.

Tittonell, P., Muriuki, A., Shepherd, K. D., Mugendi, D., Kaizzi, K., Okeyo, J., Verchot, L., Coe, R., and Vanlauwe, B. (2010). The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of east africa–a typology of smallholder farms. *Agricultural systems*, 103(2):83–97.

Tittonell, P., Vanlauwe, B., Leffelaar, P., Rowe, E. C., and Giller, K. E. (2005). Exploring diversity in soil fertility management of smallholder farms in western kenya: I. heterogeneity at region and farm scale. *Agriculture, ecosystems & environment*, 110(3-4):149–165.

Ton, G., Klerkx, L., de Grip, K., and Rau, M.-L. (2015). Innovation grants to smallholder farmers: Revisiting the key assumptions in the impact pathways. *Food Policy*, 51:9–23.

Valente, T. W. and Rogers, E. M. (1995). The origins and development of the diffusion of innovations paradigm as an example of scientific growth. *Science communication*, 16(3):242–273.

Van Diepeningen, A. D., De Vos, O. J., Korthals, G. W., and van Bruggen, A. H. (2006). Effects of organic versus conventional management on chemical and biological parameters in agricultural soils. *Applied soil ecology*, 31(1-2):120–135.

Wibowo, D. H. and Byron, R. N. (1999). Deforestation mechanisms: A survey. *International Journal of Social Economics*.

Willer, H. and Lernoud, J. (2017). Organic agriculture worldwide 2017: current statistics research institute of organic agriculture (fibl), frick, switzerland.

Wongtschowski, M., Triomphe, B., Krone, A., Waters-Bayer, A., and Van Veldhuizen, L. (2010). Towards a farmer-governed approach to agricultural research for development: lessons from international experiences with local innovation support funds. In *ISDA 2010*, pages 11–p. Cirad-INRA-SupAgro.

Wu, J. and Sardo, V. (2010). Sustainable versus organic agriculture. In *Sociology, organic farming, climate change and soil science*, pages 41–76. Springer.

Yiridoe, E. K., Bonti-Ankomah, S., and Martin, R. C. (2005). Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: A review and update of the literature. *Renewable agriculture and food systems*, 20(4):193–205.

Appendices

A Calibration and timeline of the events

Table A.1: Baseline parametrization of the model.

Parameter Description	Symbol	Value
Labor Share	α	0.8
Max Share of Wealth to Hire Workers	ζ	0.7
Labor Sensitivity to Unfilled Demand	ϵ_L	0.3
Price Sensitivity to Excess Demand	ϵ_P	0.02
Maximum Labor per Farm	L_{max}	0.5
Replicator Dynamics Intensity	ϵ_{MS}	0.5
Efficiency Weight in Fitness	ω_1	0.05
Unfilled Demand Weight in Fitness	ω_2	1 - ω_1
Demand Growth	Δ_D	4
Demand Shock Variance	σ_D	0.01
Fraction of Revenues to Innovation Expenditures	r^{IN}	0.1
Fraction of Revenues to Imitation Expenditures	r^{IM}	0.05
Innovation Lower Bound (Conventional)	θ^C_{min}	-0.2
Innovation Lower Bound (Sustainable)	θ^S_{min}	-0.2
Innovation Upper Bound (Conventional)	θ^C_{max}	0.4
Innovation Upper Bound (Sustainable)	θ^S_{max}	0.332
Innovation/Imitation Sensitivity to Innovation/Imitation Expenditure	ι	2
Ray of Observation for Imitation	d^i	1
Fraction of Imitated Farm Productivity to Own Farm Productivity	μ_{IM}	0.01
Fraction of Leading Farm Productivity to Own Farm Productivity in Within-Firm Learning	μ_{IM}	0.01
Bidding Sensitivity to Spatial Distance	ϵ_A	0.3
Fraction of Wealth Bid Amount	Ξ	0.1
Unfilled Demand Time Window when Bidding	s^u	5
Rental Price of Land Shock Variance	σ_r	0.05
Virgin Land Productivity Gain	Δ^f	0.05
Time to Reforest	T^f	50
Deforesting Sensitivity to Unfilled Demand	ϵ_f	0.1
Ray of Observation when Switching Agricultural Regime	d^s	2
Switching Intensity	τ	1
Switching Time Window	q	30
Memory when Switching Agricultural Regime	m	30
Soil Degradation Lower Asymptote	A	0
Soil Degradation Upper Asymptote	K	0.1
Soil Degradation Speed	b	0.045
Soil Degradation Lateness	M	170

Table A.2: Baseline initialization of the model.

Productivity Mean	Productivity Variance	Sustainables Penalty	Share Sustainables	Labor	Grid Size
2	1	30%	25%	0.5	225
Wealth	**Share Forests**	**Price Food**	**Demand**	**Wage**	**Price Land**
120	16%	13	225	1.5	2

Timeline of the events

At every time step t, the following events take place in chronological order:

1. Firms engage in innovation and imitation activities, and diffuse knowledge and production techniques across their farms;
2. Firms hire workers and start producing;
3. Market opens, price is determined by demand and supply, and firms' market shares are updated accordingly;
4. Profits are computed. Firms with negative liquid assets go bankrupt; their land is possibly allocated to surviving firms via auctions, or it is abandoned;
5. Land-use dynamics result from firms' decisions. Firms decide whether to a) allocate each plot of land to intensive or sustainable agriculture according to their productivity in turn is affected by human-induced soil erosion and regeneration; b) deforest pristine lands; or c) abandon unproductive farms. Reforestation can take place in abandoned lands.

B Additional equations

Food production

The homogeneous bundle of food Y_{it} is produced combining land (S_{it}) and labor (L_{it}):

$$Y_{it} = \theta_{it} L_{it}^{\alpha} S_{it}^{1-\alpha}, \tag{B.1}$$

with $0 < \alpha < 1$. Farm productivity is given by θ_{it}. Without loss of generality, assuming one farm per cell implies the normalization $S_{it} = 1$. Firm production is simply $Y_{zt} = \sum_{i \in P_{zt}} Y_{it}$, where P_{zt} is the set of farms owned by firm z at time t.

Farm productivity and technical progress

The evolution of farm productivity depends on innovation and imitation activities.
Innovation: Farm i allocates a portion r^{IN} of its revenues from the preceding period to the resource-intensive task of exploring alternatives to enhance productivity:

$$\text{EXP}_{it}^{IN} = r^{IN} S_{it-1} p_{t-1}^{food}, \tag{B.2}$$

where S_{it-1} and p_{t-1}^{food} are respectively past sales and food price. The allocation of resources to search activities increases the probability of innovation, determined by a draw from a Bernoulli distribution:

$$\text{Prob}(Innovation) = 1 - exp\left(-\iota EXP_{it}^{IN}\right), \tag{B.3}$$

where ι governs the effectiveness of innovation expenditures. The actual gain IN_{it} is drawn from a symmetric Beta(α, β) distribution.

Imitation: Similarly to innovation, farms also devote a fraction r^{IM} of their revenues to *imitation* activities

$$\text{EXP}_{it}^{IM} = r^{IM} S_{it-1} p_{t-1}^{food}, \tag{B.4}$$

which increase their chances of successfully imitating.

$$\text{Prob}(Imitation) = 1 - exp\left(-\iota EXP_{it}^{IM}\right). \tag{B.5}$$

The imitating farm first determines a set of neighbouring farms N_{it}^{IM} within a given distance d^i. [12] When imitating, the farm gets closer, in terms of productivity, with respect to the most productive farm observed in N_{it}^{IM} (see θ_{it}^{IM} in Equation B.8):

$$\theta_{it}^{IM} = \begin{cases} max(\theta \in N_{it}^{IM}) & \text{if } max(\theta \in N_{it}^{IM}) \geq \theta_{it-1} \\ \theta_{it-1} & \text{if } max(\theta \in N_{it}^{IM}) < \theta_{it-1}. \end{cases} \tag{B.6}$$

Within-farm learning: Farms under the ownership of the same firm z - i.e. belonging to the set P_{zt} - converge towards the most productive farm within P_{zt} at no additional cost (see θ_{it}^{W} in Equation B.8):

$$\theta_{it}^{W} = \begin{cases} max(\theta \in P_{zt}) & \text{if } max(\theta \in P_{zt}) \geq \theta_{it-1} \\ \theta_{it-1} & \text{if } max(\theta \in P_{zt}) < \theta_{it-1}. \end{cases} \tag{B.7}$$

Innovation is assumed to increase farm productivity regardless the outcome of the imitation process. Imitation augments current productivity through a linear combination of the past productivity of the firm itself and that of the imitated firm. An identical mechanism regulates the impact of within-firm learning. The evolution of farm productivity thus reads:

$$\theta_{it} = (1 - \mu_{IM} - \mu_W)\theta_{it-1} + \mu_{IM}\theta_{it}^{IM} + \mu_W \theta_{it}^{W} + \text{IN}_{it}. \tag{B.8}$$

where μ_{IM} and $-\mu_W$ represent gains from imitation and within-firm learning activities.

[12] The metric employed (explicitly defined in Coronese et al., 2023) is simply given by the number of nodes (cells corners) or sides separating the two cells.

Food market

Exogenous demand increases linearly, plus a random disturbance:

$$D_t = (D_{t-1} + \Delta^D)(1 + \epsilon_t^D), \tag{B.9}$$

with $\Delta^D > 1$ and $\epsilon_t^D \sim N(0, \sigma_D)$.

The price of food is influenced by disparities between supply and demand, as measured by the excess demand $\mathrm{ED}_t = \frac{D_t - Y_t}{Y_t}$. Food price increases when there is global under-production and decreases otherwise:

$$p_t^{food} = p_{t-1}^{food} \left(1 + \epsilon_p \mathrm{ED}_t\right), \tag{B.10}$$

where ϵ_p tunes price sensitivity to ED_t.

Firm market shares, denoted as MS_{zt}, follow quasi-replicator dynamics.

$$MS_{zt} = MS_{zt-1} \left(1 + \epsilon_{MS} \frac{F_{zt} - \bar{F}}{\bar{F}}\right), \tag{B.11}$$

where $F_z t$ is firm competitiveness, $\bar{F}$ is average market competitiveness, and $\epsilon_{MS} > 0$ captures the strength of selection. Firms engage in competition based on two factors: a proxy for firm (inverse) efficiency denoted as Υ_{zt} and their capability to consistently meet the demand they encounter, quantified by unfilled demand UD_{zt}. A firm's fitness F_{zt} is thus given by the inverse of a linear combination of these two factors:

$$F_{zt} = \frac{1}{\omega_1 \Upsilon_{zt} + \omega_2 \mathrm{UD}_{zt,UD>0}}, \tag{B.12}$$

with ω_1 and ω_2 governing their relative weights. Firm (inverse) efficiency is thus given by

$$\Upsilon_{zt} = \frac{1}{Y_{zt}} \sum_{i \in P_{zt}} \Upsilon_{it} Y_{it} \quad \text{with} \quad \Upsilon_{it} = (\theta_{it})^{-1} + \epsilon_{it}^{\Upsilon}, \tag{B.13}$$

where $\epsilon_{it}^{\Upsilon} \sim N(\mu_t^{\Upsilon}, \sigma^{\Upsilon})$ is a random disturbance capturing small shocks to farm productivity.[13] The unfilled demand term (UD_{zt}) is defined as:

$$\mathrm{UD}_{zt} = \frac{Y_{zt} - D_t MS_{zt}}{Y_{zt}}. \tag{B.14}$$

Production adjustment

Labor: Firms decide the amount of labor L_{zt} according to a simple rule of thumb, responding to over and under-production on the basis of the observed level of unfilled demand:

$$L_{zt} = L_{zt-1}(1 + \epsilon_L UD_{zt-1}), \tag{B.15}$$

where $\epsilon_L < 1$ tunes firms' attitude towards labor adjustment.[14] Workers hired at the firm level L_{zt} are allocated to each owned farm according to the relative productivity of the plots of land:

$$L_{it} = L_{zt} \frac{\theta_{it}}{\theta_{zt}}, \tag{B.16}$$

where θ_{zt} is the average productivity of farms owned by firm z. Each cell has a limit L^{max} to the amount of workers which can operate on it. Firms may scale down employment and production if their total wage bill is higher than a fixed share ζ of their current wealth W_{zt}:

$$L_{zt} \leq \frac{\zeta W_{zt}}{w_t}. \tag{B.17}$$

Acquisition of defaulted farms: Farms belonging to firms which go bankrupt - because of negative lliquid assets

[13] In order to keep the disturbance relevant as the economy grows, we assume μ_t^{Υ} to increase at the average rate of growth of farm productivity Δ_t^{θ}.

[14] A value of less than unit ensures stickiness in the labor market, consistently with seasonal labor contracts (Mueller and Chan, 2015).

(Equation B.23) or insufficient market share - are sold on a second-best auction. The probability of a firm placing a bid on a farm on sale depends on its spatial proximity to the farm on sale, and on the the average unfilled demand in the last s^u periods:

$$\text{Prob}(\text{BID}_{zt} = 1) = I_{zt} exp(-\epsilon^A d_{ij}) \quad \text{with} \quad I_{zt} = \begin{cases} 1 & \text{if} \quad \sum_{h=t-s^u}^{t} UD_{zh} > 0 \\ 0 & \text{if} \quad \sum_{h=t-s^u}^{t} UD_{zh} \leq 0, \end{cases} \tag{B.18}$$

where ϵ^A is a parameter and d_{ij} is the distance between the farm on sale i and the closest farm among those owned by bidder z, farm j. Each bidding firm places a bid equal to a fraction of its wealth $B_{zt} = \Xi W_z t$. If the auction goes empty, the farm is abandoned (Gellrich et al., 2007) and the soil upon which they operated is reconverted into forest after T^f periods.

Deforestation: Similarly, the probability of a firm to deforest a virgin land within a given distance d^f from one of his farms depends on perceived under-production, and is given by

$$\text{Prob}(\text{Deforesting}) = 1 - exp(-\epsilon_f \frac{1}{s^u} \sum_{h=t-s^u}^{t} UD_{zh}), \tag{B.19}$$

where ϵ_f tunes the propensity to deforest. Forests subsequently become highly productive farms, with a productivity equal to the deforesting farm plus a fixed proportion Δ^f.

Profits and land re-allocation

Farms profits (Π_{it}) are given by:

$$\Pi_{it} = S_{it} p_{it}^{food} - w_t L_{it} - r_{it}^{\ell}, \tag{B.20}$$

where r_{it}^{ℓ} is the rental price of land. It grows at the average rate of growth of soil productivity Δ_t^{θ}, i.e. $r_t^{\ell} = r_{t-1}^{\ell}(1 + \Delta_t^{\theta})$, plus a random i.i.d. disturbance $\varepsilon_{it}^r \sim N(0, \sigma_r)$, i.e.:

$$r_{it}^{\ell} = r_t^{\ell}(1 + \varepsilon_{it}^r). \tag{B.21}$$

Firms profits are simply given by

$$\Pi_{zt} = \sum_{i \in P_{zt}} \Pi_{it}. \tag{B.22}$$

Firms liquid assets (W_{zt}) are simply the cumulative sum of past profits:

$$W_{zt} = W_{zt-1} + \Pi_{zt}. \tag{B.23}$$

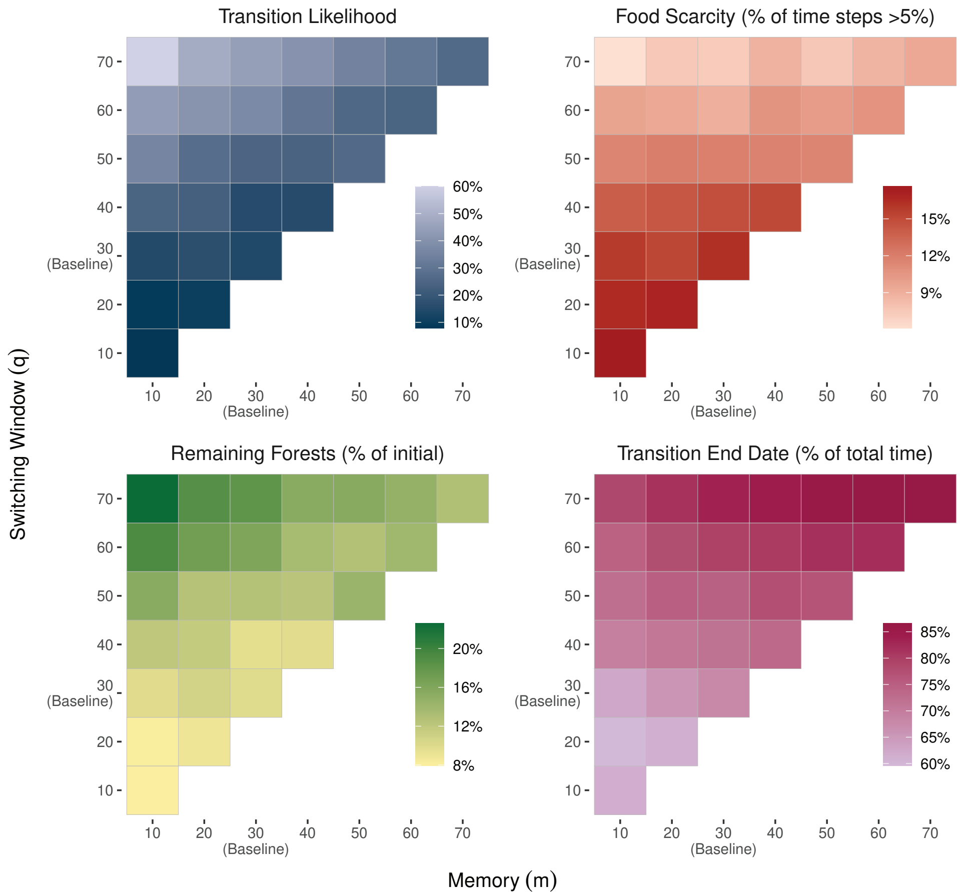
Switching dynamics

When employing output only, Equation 4 becomes

$$\gamma_{zt}^S = \frac{1}{\#(S_{zt})} \frac{1}{m} \sum_{k \in [t-m,t]}^{i \in S_{zt}} Y_{ik} \qquad \gamma_{zt}^S = \frac{1}{\#(C_{zt})} \frac{1}{m} \sum_{k \in [t-m,t]}^{i \in C_{zt}} Y_{ik} \tag{B.24}$$

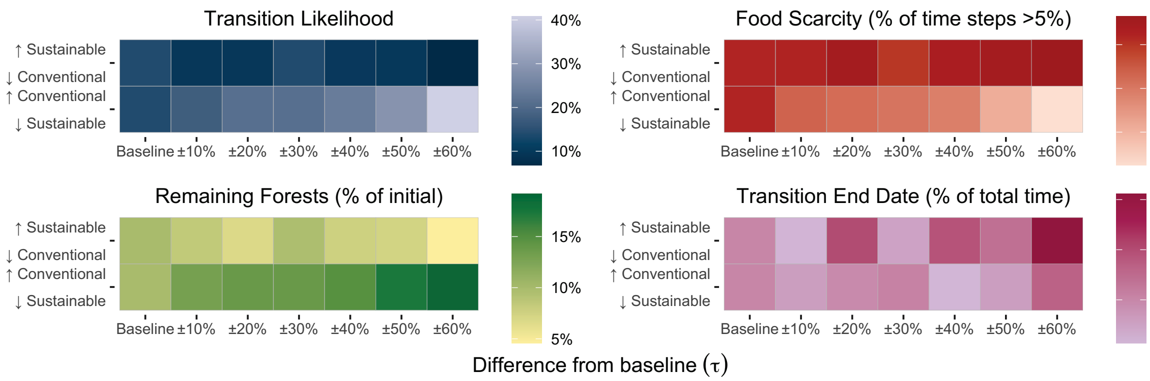
C Additional figures

Figure C.1: Heat-maps for different switching windows q and values of memory m.



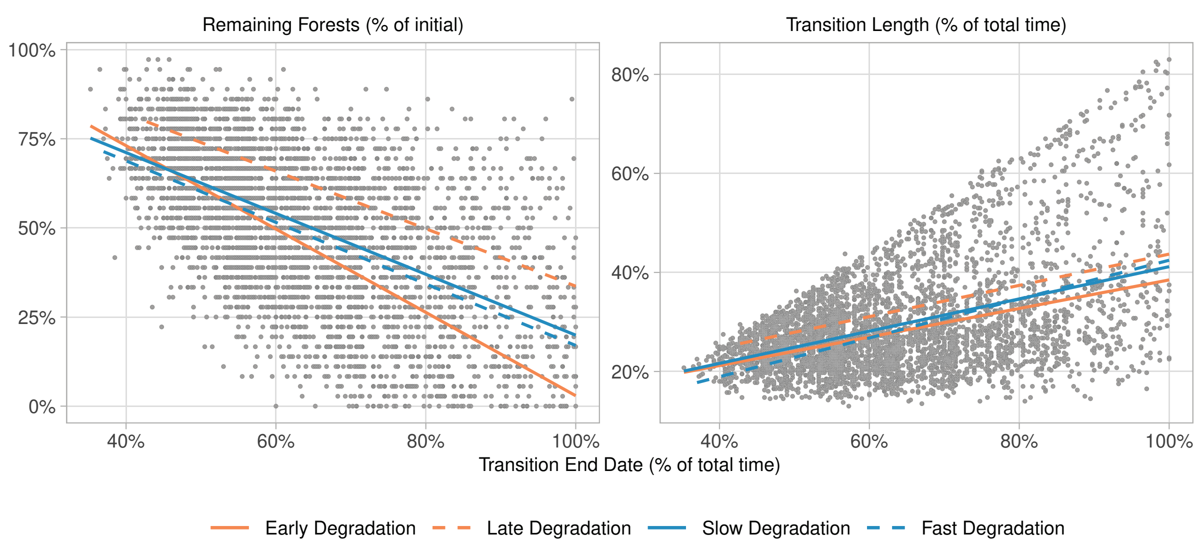
Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Transition time is given by the period in which the share of sustainable farms reaches 90%, averaged across runs which end up in a successful transition. Final excess demand and final remaining forests (i.e. at $t = 400$) are Monte Carlo averages. 100 Monte Carlo runs.

Figure C.2: Heat-maps for heterogeneous attitudes to switch τ between sustainable and conventional firms.



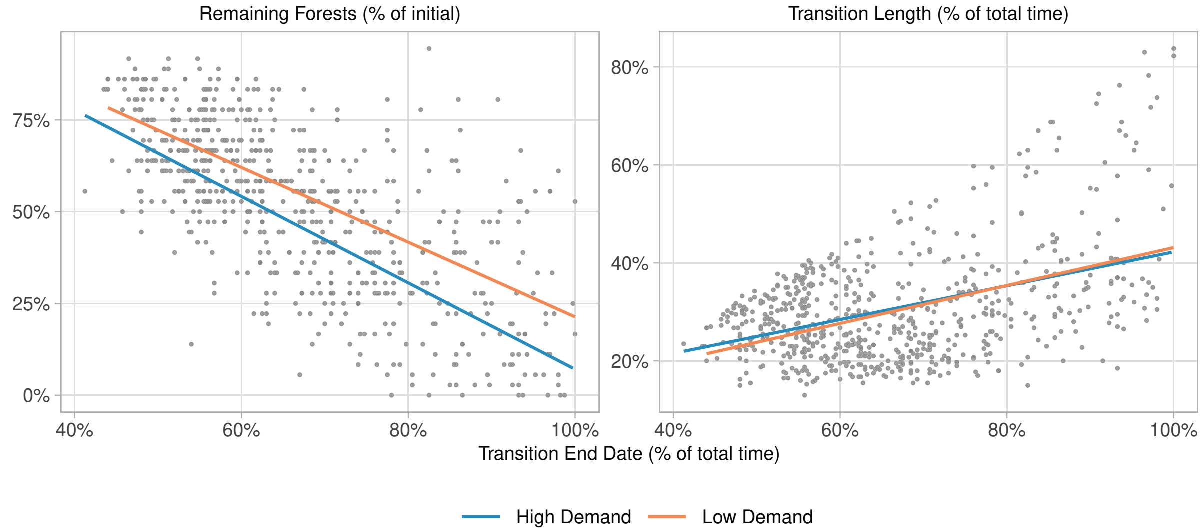
Note: Upper tiles represent scenarios in which sustainable firms' attitude to switch is a certain percentage (x-axis) higher with respect to baseline ($\tau = 1$), while conventional firms' attitude is a certain percentage lower. Lower tiles represent the opposite scenarios. Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%. Transition time is given by the period in which the share of sustainable farms reaches 90%, averaged across runs which end up in a successful transition. Final excess demand and final remaining forests (i.e. at $t = 400$) are Monte Carlo averages. 100 Monte Carlo runs.

Figure C.3: Transition end date against final share of remaining forests and transition length, for different speeds of soil degradation b and values of soil degradation earliness M.



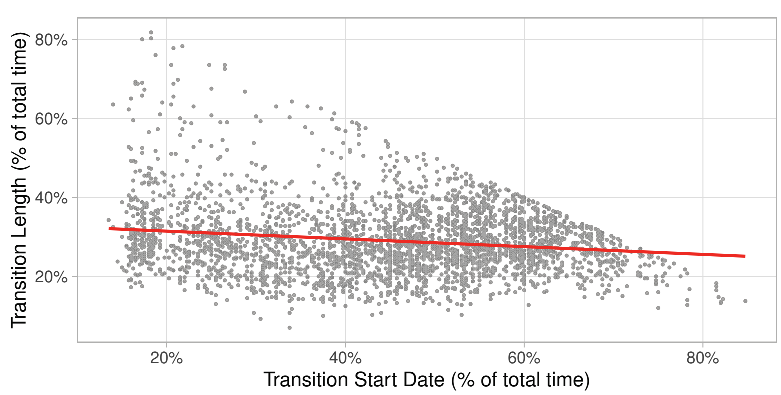
Note: Pooled runs for different values of b and M (see Figure 8). Each dot is a single run. Straight lines are OLS best-fitting lines for grouped observations. Early Degradation: $M \in \{-40\%, -20\%, \text{Baseline}\}$; Late Degradation: $M \in \{+20\%, +40\%, +65\%, +80\%\}$; all b. Slow Degradation: $b \in \{-60\%, -40\%, -20\%, \text{Baseline}\}$, Fast Degradation: $d^s \in \{+20\%, +40\%, +60\%\}$; all M. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, expressed as percentage of simulation length. Length is defined as the difference between start and end date, expressed as percentage of simulation length. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry.

Figure C.4: Transition end date against final share of remaining forests and transition length, for different rate of growth of food demand Δ_D.



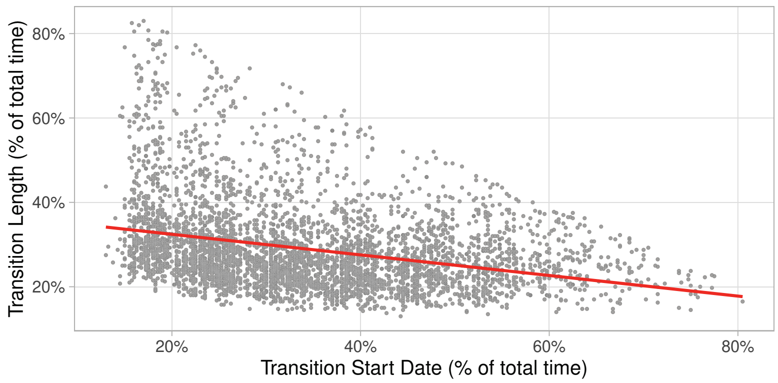
Note: Pooled runs for different values of Δ_D (see Figure 9). Each dot is a single run. Straight lines are OLS best-fitting lines for grouped observations. Low Demand: $\Delta_D \in \{-25\%, -20\%, -10\%, -5\%, \text{Baseline}\}$; High Demand: $\Delta_D \in \{5\%, +10\%, +20\%, +25\%\}$. End date is equal to the earliest time step at which the share of sustainable farms surpasses 90%, expressed as percentage of simulation length. Length is defined as the difference between start and end date, expressed as percentage of simulation length. Remaining forests (i.e. at $t = 400$) are expressed as a share of initial stock of forestry.

Figure C.5: Transition start date against transition length, for different observational horizons d^s and attitudes to switch τ.



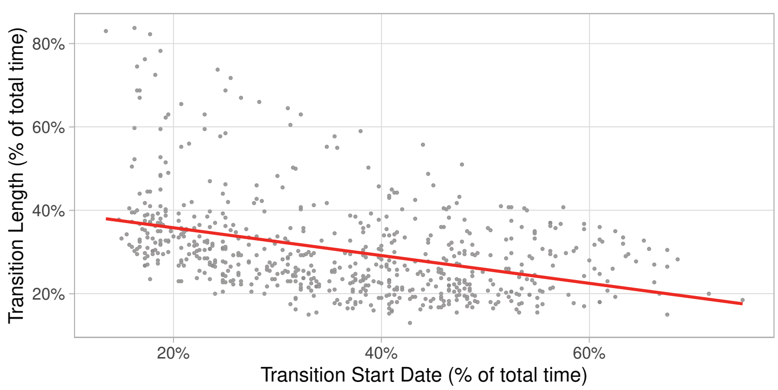
Note:

Figure C.6: Transition start date against transition length, for different speeds of soil degradation b and values of soil degradation earliness M.



Note:

Figure C.7: Transition start date against transition length, for different rate of growth of food demand Δ_D.



Note: