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Analysis

AgriLOVE: Agriculture, land-use and technical change in an evolutionary, agent-based model

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ABSTRACT

This paper presents a dynamic agent-based model of land use and agricultural production under environmental boundaries, finite available resources and endogenous technical change. In particular, we model a spatially explicit smallholder farming system populated by boundedly-rational agents competing and innovating to fulfill an exogenous demand for food, while coping with a changing environment shaped by their production choices. Given the strong technological and environmental uncertainty, agents learn and adaptively employ heuristics which guide their decisions on engaging in innovation and imitation activities, hiring workers, acquiring new farms, deforesting virgin areas and abandoning unproductive lands. Such activities in turn impact farm productivity, food production, food prices and land use. We firstly show that the model can replicate key stylized facts of the agricultural sector. We then extensively explore its properties across several scenarios featuring different institutional and behavioral settings. Finally, we simulate the model across different applications considering deforestation and land abandonment; human-induced soil degradation; and climate impacts. AgriLOVE offers a flexible simulation environment to study the endogenous emergence of different agricultural production regimes from the interaction of spatially dispersed farms subject to resource constraints, spatial influence and climate change.

1. Introduction

This paper presents a novel agent-based model (ABM) of the agricultural sector. The model, labeled AgriLOVE (Agriculture and Land Organization in an eVolutionary Economy), comprises spatially-located, heterogeneous, bounded 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. The model targets a smallholder farming system and can be employed to perform scenario analyses featuring different climates, institutional and policy settings (as in e.g. Bert et al., 2011; Berger and Troost, 2014). This paper aims to investigate how agricultural productivity — and the emergence of food scarcity and rising agricultural prices in particular — is affected by the interplay of market selection, learning and the spatial allocation of resources. In particular, we study how such mechanisms shape deforestation dynamics, human-induced soil depletion and the recovery from climate-related shocks.[1]

Agriculture is the major destination of land use across the globe (Foresight, 2011). To meet projected growth in human population and per capita food demand, historical increases in agricultural production will have to continue until the end of the century (Howden et al., 2007). Both land clearing and more intensive use of existing croplands substantially contributed to increase food supply, while reducing its price. However, population and consumption growth have raised competition for land, water and other resources, thus rising environmental concerns related to the sustainability of current agricultural patterns (Godfray et al., 2010a,b). During the last 60 years, global population growth and changes in per-capita consumption of food, feed, fiber, timber and energy have caused unprecedented rates of land and freshwater usage, contributing to increasing net greenhouse gas emissions, loss of natural ecosystems (e.g., forests, savannas, natural

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[1] In principle, the model can also be calibrated to particular areas to perform fine-grained impact and policy analysis (as in e.g. Troost and Berger, 2015), though we leave such exercises to future research.

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grasslands and wetlands) and declining biodiversity (Intergovernmental Panel on Climate Change, 2022).

In the convolutions of the present Anthropocene era (Steffen et al., 2015), the intersections between agricultural production, land use needs, limited resources and incumbent climate change call for systemic solutions, which must reflect the non-linear interplay between environment and human activity. The inherent complexity of modern economies (Arthur, 1999), and of their interaction with surrounding environment, requires approaches able to capture the essential features of such composite structures. Previous models in the domain of agricultural economics have shown that agent-based models are natural candidates to explore complex socio-ecological systems (Filatova et al., 2013; Berger, 2001; Bert et al., 2011; Berger and Troost, 2014).

Contributing to this literature, the AgriLOVE model provides a laboratory for the analysis of trade-offs between the increasing need for agricultural output and the constraints imposed by limited resources and their potential degradation from the bottom-up. Specifically, it investigates the roles of (i) market selection and concentration, (ii) learning and technical change and (iii) spatial agglomeration in affecting agricultural productivity, food production and food prices in a smallholder farming system with environmental boundaries. AgriLOVE complements the blossoming literature of micro-calibrated agent-based models of agriculture and land use. While many studies focus on highly specific regions and climatic conditions, we offer a system-wise perspective allowing to compare endogenously emerging regimes of agricultural production and their stability to alternative institutional and behavioral settings in the short and in the long run. The model accommodates several mechanisms of environment-agent interactions as well as agents' behavioral attitudes, and allows the analysis of various scenarios of farm productivity degradation, forest and land management, population growth and climate impacts on farmers' activities. Building on the evolutionary theory of agricultural modeling (Janssen and Ostrom, 2006; Berger and Troost, 2012), we populate our model with boundedly-rational, locally-interacting agents that compete on a centralized market characterized by imperfect information in order to satisfy an increasing global demand. Agents adaptively react to the perceived state of the system, dynamically adjusting production, inputs, technology and land usage (e.g. by abandoning unprofitable crops or deforesting virgin areas). Productivity gains arise as the result of a stochastic process of innovation, as well as through local imitation and knowledge spillovers from clusters of farms. As argued in Moser (2020) and Ruttan (1997) among others, research, innovation, and knowledge diffusion are key determinants of the short and long run dynamics of agricultural yields.

In its baseline configuration — which excludes human-induced soil depletion and climate shocks — the model reproduces a linear growth in total agricultural output, as the result of an increase in productivity stemming from the heterogeneous innovation and imitation activities occurring at the micro level. Such secular increase is coupled with a declining sectoral employment in agriculture and a decreasing price of food. The foregoing dynamics can be studied under different resource and environmental constraints, providing a systemic analysis of how "institutional" and behavioral factors can modify such trajectories. Indeed, we show how different levels of local imitation and knowledge spillovers influence macro-level structural outcomes of the system, such as the distributions of farm size and farm productivity. We further show how the non-trivial spatial structure of the model allows the emergence of bi-modalities in land productivity in line with the well-established evolutionary literature on agricultural economics — see among others, Balmann (1997), Balbi et al. (2013).

Our simulation results show that (i) imitation among spatially close farm critically boost aggregate productivity, and reduces market concentration, (ii) transfer of knowledge among associated farms successfully reduces productivity dispersion, (iii) spatial segregation and bi-modalities in farm productivity can emerge endogenously, as a consequence of both high-market selection as well as land productivity clustering. In addition, we study different applications of the model. First, we allow for deforestation and land-abandonment showing that profit incentives can lead to increasing rates of pristine soil exploitation which ultimately reduce total crop production. We then study the effects of human-induced soil degradation on sustainable transition dynamics, highlighting a poor capacity of the agricultural system to cope with approaching environmental boundaries, in absence of appropriate policies. Finally, we investigate the consequences of climate-related shocks, showing non-trivial spatial propagation effects and emergent hysteresis.

The paper is organized as follows: Section 2 discusses the model in the perspective of the current existing literature. Section 3 describes the model in details and offer a schematic overview of its code. In Section 4, we present simulation results showing the main properties of the model, along with the micro and macro stylized facts it is able to replicate and possible applications. Finally, Section 5 concludes the paper. In this section we offer a critical evaluation of model limitations and most simplifying assumptions, further describing how we envision to address them in future research, together with a discussion of parallel future developments and applications.

2. Related literature and contributions

Models of land use investigate the complexities stemming from socio-economic and biophysical factors that influence and are influenced by the spatial pattern of land-use changes (Ustaoglu and Aydinoglu, 2019; Verburg et al., 2004). The simulation of land use change and adaptation in agricultural systems dates back to recursive linear programming models for farm policy analysis (Schreinemachers and Berger, 2011) — see, for an example, the work of Day and Singh (1975). Other methods of representation include cellar-automata models with agents characterized by heterogeneous beliefs and behaviors (e.g. Mathevet et al., 2003), machine-learning and neural networks models (e.g. Deffuant et al., 2005). Extensive reviews on this composite literature have been carried out by Elsawah et al. (2020), Le Page et al. (2017), Luus et al. (2013) and Utomo et al. (2018).

Agent-based modeling (ABM) is an approach that has been receiving attention by the land use modeling community in recent decades. ABM offers a way of incorporating the influence of human decision-making on land use in a mechanistic and spatially explicit way, taking into account social interaction, adaptation, and decision-making at different levels (Matthews et al., 2007). The work of Lansing and Kremer (1993) and, even more, Balmann (1997) and Berger (2001) laid the foundation to the use of agent-based simulations in the domain of agricultural economics and land use. Since then, a number of agent-based land use models have been developed — see reviews by Parker et al. (2003), Bousquet and Le Page (2004) and Berger and Troost (2014). There has been a gradual progression of such models from relatively abstract representations, which were used to explore aspects of spatially explicit systems (e.g. Epstein and Axtell, 1996), to more complex representations of socio-ecological systems (e.g. Berger and Ringler, 2002) based on empirical data (e.g. Berger et al., 2007; Carauta et al., 2021). The ABM literature on agriculture and land-use is vast and has been blossoming in recent years covering, among others, studies on (i) emerging dynamics of agricultural interactions (e.g. Parker et al., 2003); (ii) water management and resource-sharing mechanism (e.g. Tesfatsion et al., 2017; Gurung et al., 2006); (iii) forest management and agricultural policies (e.g. Nute et al., 2004); and (iv) food production and environment interactions (e.g. Happe et al., 2006; Barnaud et al., 2007; Bert et al., 2011). A key contribution in this stream of models is the multi-agent system of human–environment interactions (Berger et al., 2006), identified by the authors with the MP-MAS acronym. Relying on a robust micro economic foundation and the calibration on empirical data, MP-MAS models combine social network effects with an economic evaluation of technologies to adopt. However, the sources of innovation are exogenous and independent of market conditions and agricultural production regimes. In these simulators, agents are boundedly-rational, can update price expectations and can exchange resources on local markets. Depending on the availability of empirical data, MP-MAS models can be flexible in the use of biophysical modules. The framework of MP-MAS has been successfully applied to study the rural economy of Mato Grosso in Brazil, Maule Basin in Chile, White Volta Basin in Ghana, Central and Southeast Uganda and in multiple locations across Ethiopia.

Stemming from the MP-MAS tradition and the overall flourishing literature of land use ABM — for a detailed review, see Kremmydas et al. (2018) and Utomo et al. (2018) — the AgriLOVE model is conceived as a complementary tool with respect to existing frameworks. First, it explores bottom-up macro-level dynamics and their unfolding over long-run horizons; in that, our model allows studying the emergence of novel (stable or unstable) regimes of agricultural production as a result of farmers' interactions in markets and space. This features enables a more complete understanding of the possible futures of smallholder agricultural economies, though the model does not offer quantitative predictions yet. In this sense, this paper aligns to what Nelson (2016) describe as fruitful economic modeling: the construction of allegories that can help thinking and the understandings of the systems under investigation. Second, AgriLOVE merges a spatial agricultural economy with boundedly-rational agents whose behaviors are genuinely routinized. Differently from other modeling traditions, e.g. Berger (2001) and subsequent contributions or Morgan and Daigneault (2015),[2] farmers in AgriLOVE do not optimize any utility or profit functions, neither dynamically nor myopically; rather, they evolutionary strive to adapt their decision routines (e.g. how to hire workers and which prices to set) to improve upon the status-quo. This feature creates a direct link between AgriLOVE and evolutionary modeling of organizational behavior (Nelson and Winter, 1982; Zollo and Winter, 2002). Along these lines, we aim at contributing to the agricultural economics ABM literature featuring agents' dynamics dictated by both spatial proximity (as in Thebaud et al., 2001) and social proximity (as in Janssen, 2007; Courdier et al., 2002). Third, AgriLOVE includes an endogenous — though stylized — process of technical change, encompassing search for innovations and knowledge diffusion as key drivers of long run farm productivity. We believe this contrasts a number of existing land use models, wherein sources of productivity and yield growth are exogenous.[3] This feature allows studying the feedback loops between technical change, market structure, production and the spatial patterns of land use. The process of search for innovation and its fundamental uncertainty is inspired by evolutionary theories of technical change (Nelson and Winter, 1982; Dosi et al., 1988, 1995; Dosi and Nelson, 2010; Silverberg et al., 1988; Fagiolo and Dosi, 2003). Finally, by depicting a system encompassing growth, land use and markets subject to different degrees of imperfections, AgriLOVE offers a simulation laboratory to investigate, at least qualitatively, the institutional settings and policy interventions determining the emergence of sustainable patterns of food production, food prices and environment preservation. Indeed, reviews show that — without exploring further how overall dynamics and trade-offs within smallholder farming systems develop — it is hard to conceive policies able to support and increase the viability of a variety of farms with different scales of operation (Giller et al., 2021). To conclude, AgriLOVE can be employed to investigate the system-wise implications of climate change impacts on agricultural production (for a review, see Matthews et al., 2007; An, 2012; Groeneveld et al., 2017; Müller et al., 2020).[4] Other climate-agriculture ABM models have been extensively used to study scenarios of supply responses, ex-ante policy testing and the effectiveness of adaptation strategies (Berger and Troost, 2014), both through thought-experiments and specific applications (e.g. Berger et al., 2017). Indeed, its modular structure allows coupling it with the family of recently developed agent-based integrated assessment models (Balint et al., 2017; Lamperti et al., 2018, 2019b, 2021), which currently lack representation of land use and cover change dynamics and related emissions. This would allow obtaining a complete, fully-fledged integrated assessment agent based model.

3. The AgriLOVE model

The structure of the economy portrayed by the model is described in Fig. 1. The model is populated by an ecology of N_t smallholder agricultural firms, which can own a variable number of farms, thus possibly cultivating multiple plots of land. This dual terminology is consistent with Moser (2020). Farms combine land and labor to produce a homogeneous bundle of food — a representative crop ideally composed only by cereals. Farms can improve their productivity through various mechanisms, including innovation, local imitation and knowledge spillovers among farms belonging to the same firm (within-firm learning). Firms sell collected food on a centralized market, characterized by imperfect information and subject to an exogenous demand. Firms learn and adapt to their market performance through different feedback mechanisms, including labor hiring, innovation expenditures, and decisions about whether to abandon a certain plot of land or to deforest a virgin one.

The representation of a homogeneous bundle of food can be assimilated to the energy yield (kilo-calories/ha) concept, widely used in the agricultural literature — among others, see Grassini et al. (2013). We focus on cereal production (i.e. maize, wheat, soybean and rice), given its relevance in terms of food security (FAO, 2017b) and land use, with cereals occupying more than half of world's harvested area.[5] Additionally, cultivating and harvesting cereals-alike crops do retain around 50% of total carbon emissions attributed to the agricultural sector (Tubiello et al., 2015; IPCC, 2010).

Land is represented as a physical space captured by a two-dimensional, regular cell grid. Each cell represents either: (i) a *forest*, i.e. a virgin area not comprising any agricultural activity; (ii) a plot of *arable land* which can be exploited by a farm for food production; (iii) *abandoned land* which is no longer cultivated for its scarce profitability. The typical map of the model is shown in Fig. 2. Cell grid representation allows a better spatial representation of climate impacts, as well as a more realistic picture of the system interactions — see e.g. Jones et al. 2017. Indeed, physical distances are crucial in shaping interaction dynamics in agriculture. The model is endowed with a metric $d_{i,j}$, used to compute distances between two cells (or farms) i and j. The distance is simply given by the number of nodes (cells corners) separating the two cells.[6] Thus, if farm i has a ray of observation $r = 1$, the set of observed neighbors is simply represented by the square of cells surrounding cell i, while if $r = 2$, the set of observed neighbors would then include also the square of cells surrounding those immediately adjacent to the farm itself.

[2] See also Huber et al. (2018) for a survey of decision making protocols in European agriculture ABMs.

[3] Admittedly, AgriLOVE lacks a proper adoption and diffusion dynamics of novel inputs, which is part of various land use models (e.g. Berger and Troost, 2014; Evans et al., 2011) and we plan to include in future research.

[4] Examples of models addressing this issue are Deadman et al. (2000) for forest management and of Dean et al. (2000) for agricultural land management.

[5] Furthermore, focusing on cereals allows us to avoid peculiar distortions present in the production of e.g. vegetables, wine, biofuels and livestock agricultural markets.

[6] Alternatively, the similar and more canonical Manhattan metric can be easily implemented without substantially altering the main properties of the model.

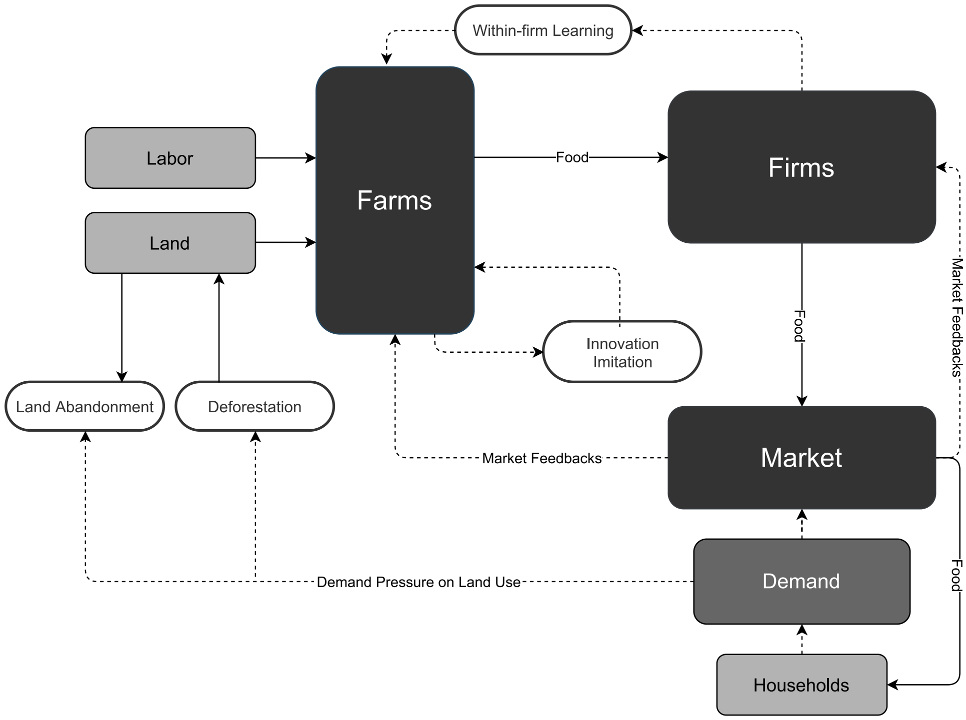

Fig. 1. Workflow of the model.

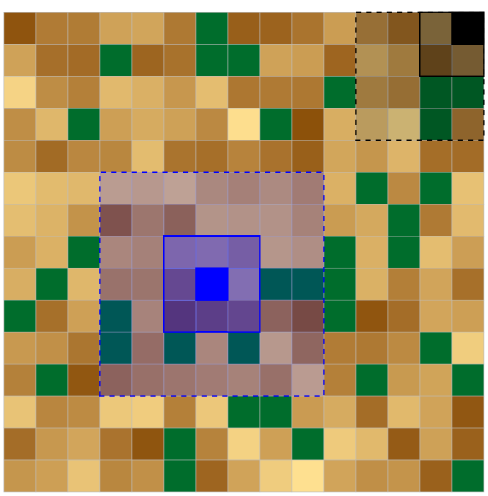

Fig. 2. Different observational horizons ($d = 1$ and $d = 3$) from distinct locations on the lattice. Darker cells have higher soil productivities, green cells are forests.

3.1. Timeline of the events

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

1. Firms engage in innovation and imitation activities, and diffuse knowledge and productive technologies across their farms (Section 3.2);
2. Firms hire workers and start producing (Section 3.3);
3. Market opens, price is determined by demand and supply, and firms' market shares are updated accordingly (Section 3.4);
4. Profits are computed (Section 3.5). 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 (Section 3.6.2); (b) deforest pristine lands; or (c) abandon unproductive farms. Reforestation can take place in abandoned lands. (Section 3.6.1).

Appendix A contains the details on the structure of the code.

3.2. Innovation, imitation and farm productivity dynamics

Firms (indexed by z) own farms (indexed by i), which are in turn characterized by a farm-specific productivity θ_{it}. Each farm has an initial soil productivity θ_{i0}, mimicking the heterogeneously-distributed, predetermined pedo-climatic characteristics (Fatichi et al., 2020) of the plots of land upon which they operate (Fig. 2). In order to increase their profits, agents strive to improve farm productivity by innovating, imitating neighboring farms, and learning the best agricultural practices and techniques (e.g. Conforti, 2017).

Innovation activities in the model are intended as all those practices and procedures which attempt to increase farm productivity. Gains in productivity in smallholder settings often comes from a variety of sources, including: (i) improved crop and seed varieties, access to blended fertilizers and integrated pest management practices; (ii) increase in land management and soil quality; (iii) changes in operational routines, acquisition of new skills and management capabilities. Thus, innovation activities can be though as contributing to the amelioration of both soil productivity (by e.g., virtuous soil management practices which contribute to soil health like mulching, nutrients restoration and agroforestry) as well as aspects related to the efficiency of farming techniques (e.g., increased input quality, irrigation techniques, organizational routines). The model does not distinguish explicitly these three mechanisms, and a gain in productivity reflects a generic improvement in at least one of these dimensions. We model innovation as a technology-based process (Coomes et al., 2019), through a two-step costly process. First, farms devote a fraction r^{IN} of their past revenues to the process of search for productivity enhancing innovations:

$$\mathrm{EXP}_{it}^{IN} = r^{IN} S_{it-1} p_{t-1}^{food}, \tag{1}$$

where S_{it-1} represents sales (in terms of bundles of food) and p^{food}_{t-1} is the lagged price of food. EXP^{IN}_{it} proxies search efforts and search costs for new inputs and new routines the farm could potentially employ. For instance, access to new seeds involve costs related to time-consuming information gathering, as well actual spending for their purchase. Differently, practices intended to improve soil quality require resources (e.g. training) to be implemented, while changing routines, acquiring new skills, and experimenting with alternative production techniques and organizational setups are all costly activities (see Nelson and Winter, 1973, for a seminal work on this topic). A higher search effort EXP^{IN}_{it} increases the chance of successfully innovating. Whether a farm successfully innovate, is determined through a Bernoulli trial, with probability

$$\text{Prob}(Innovation) = 1 - exp\left(-\iota EXP^{IN}_{it}\right), \tag{2}$$

where the parameter ι captures the effectiveness of innovation expenditures, as in Dosi et al. (2010).[7] The stochastic nature of this process reflects the intrinsic uncertainty about the actual success of the evolutionary process of search for innovations. New inputs might not be found, or collected information may not be substantial enough to lead to an actual implementation; similarly, attempts of changes in organizational routines might fail.[8] In case of successful innovation, the productivity improvement entailed by the new practice IN_{it} is drawn from a symmetric $Beta(\alpha, \beta)$ distribution, whose support is $[\theta_{min}, \theta_{max}]$, with $\theta_{min} < 0$ and $\theta_{max} > 0$. The parameters and the support of the $Beta$ distribution jointly regulates the set of technological opportunities farms can capture.[9] Differently from the first stage, the presence of uncertainty here reflects the idea that the impact of innovations on productivity cannot be known *a priori*. 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).

Imitation is an extremely common practice among smallholder farming systems: social networks (Manson et al., 2016), peer-learning mechanisms (Conley and Udry, 2010; Bandiera and Rasul, 2006), as well as competitors' mimicking unlock technology adoptions. Alike innovation, imitation is modeled as a two-steps process, and is assumed to be a costly process, reflecting similar search and effort costs, as well as set-up costs for the introduction of new techniques (MacLeod et al., 2005), barriers (e.g. educational and institutional) to imitation (Brenner, 2006), workers' training, and traveling to trade fairs and markets. Farms allocate part of their revenues r^{IM} to imitation:

$$\text{EXP}^{IM}_{it} = r^{IM} S_{it-1} p^{food}_{t-1}. \tag{3}$$

Naturally, $r^{IN} + r^{IM} \leq 1$. The probability of successfully imitating is regulated again by a Bernoulli trial, with probability[10]

$$\text{Prob}(Imitation) = 1 - exp\left(-\iota EXP^{IM}_{it}\right). \tag{4}$$

Alongside with other factors (e.g. physical infrastructures and social networks), geographical proximity still plays a major role in shaping imitation dynamics in smallholder farming cropping systems (Tirkaso and Hailu, 2022; Moss et al., 2000). Therefore, imitation happens between spatially close farms (Pomp and Burger, 1995, see Section 3.6.2 for technological proximity). Spatial distance is defined using the metric described at the beginning of Section 3. If imitation is successful, farm i defines the set of neighboring farms N^{IM}_{it} within a given ray d^i (cf. Fig. 2), and it selects the most productive farm in N^{IM}_{it}:

$$\theta^{IM}_{it} = \begin{cases} max(\theta \in N^{IM}_{it}) & \text{if } max(\theta \in N^{IM}_{it}) \geq \theta_{it-1} \\ \theta_{it-1} & \text{if } max(\theta \in N^{IM}_{it}) < \theta_{it-1} \end{cases} \tag{5}$$

The imitating farm is then allowed to get closer to the imitated farm in the technological space (see Eq. (6) below), in a process of technological catch-up. Finally, farms engage in *within-firm learning* activities, a different kind of imitating behavior involving the transfer of knowledge and techniques between farms belonging to the same firm. This process mimics knowledge exchanges observed, for example, in the case of family or group-owned farms, where plots of a single producer are rented out (formally or informally) to family or group members (Tittonell et al., 2010). Without any additional cost, each farm is allowed to mimic the most productive one among those belonging to the same firm. If pure imitation involves a geographically-based, horizontal mechanism of acquisition of knowledge (Foster and Rosenzweig, 1995), within-firm learning features a figurative top-down vertical process (Swinnen, 2007) of knowledge transfer within the farms of a same firm.

Overall, the dynamics of farm productivity (θ_{it}) are affected by innovation, imitation and within-firm learning. We assume that the knowledge acquired across these three processes allows farms to improve their productivity. First, if imitation is successful, the productivity of farm i at period t is expressed as a linear combination of its first lag and the target θ^{IM}_{it}. An analogous mechanism governs the influence of the most productive farm within each firm (θ^{W}_{it}). Second, innovation is assumed to boost productivity independently from the outcome of the imitative process. Hence, productivity dynamics reads

$$\theta_{it} = (1 - \mu_{IM} - \mu_W)\theta_{it-1} + \mu_{IM}\theta^{IM}_{it} + \mu_W \theta^{W}_{it} + \text{IN}_{it}. \tag{6}$$

where the parameter μ_I is defined in the open interval between zero and one, and captures the speed of knowledge transfer from the imitating or within-firm learning activities. This formulation resembles setups displaying strong synergies among technological alternatives,[11] and allows us to jointly explore the contribution of both imitative processes to the model dynamics (see Section 4.2.1, Appendix C, and Appendix D). Of course, a variety of alternative laws of motion for farm productivity are possible, depending on whether innovative efforts, imitation and learning are treated as complements or substitutes.[12]

3.3. Crop production

The production process combines land (S_{it}) and labor (L_{it}) to produce a homogeneous bundle of food. Production (Y_{it}) takes place at the farm level according to the following equation:

$$Y_{it} = \theta_{it} L^{\alpha}_{it} S^{1-\alpha}_{it}, \tag{7}$$

[7] We normalize expenditures with respect to the expenditure frontier. This ensures that innovation probability do not mechanically increase with economic growth.

[8] In this sense, an example is provided by the practice of row planting, which frequently allows farms to largely improve their productivity. Rates of adoption of this technique, which involves costly changes in labor tasks and organizational setups, has been indeed consistently low in numerous smallholders cropping systems despite such technique was known as an available option (Tamirat and Abafita, 2021).

[9] Note that innovation may fail, entailing lower productivity and higher costs with respect to those previously employed (Dosi et al., 2010). Indeed, failed innovations in the agricultural sector are a fairly common phenomenon among smallholder farmers and often stem as an underestimation of non-technological factors, such as social components (Peters et al., 2018), as well as monetary constraints and farmers' predispositions (Razanakoto et al., 2018).

[10] Similarly to innovation, we normalize expenditures with respect to the expenditure frontier.

[11] For example, there is evidence that smallholder farmers in sub-Saharan Africa explore new technological options which are displaying intrinsic synergies (Sunding and Zilberman, 2001; Chavas and Nauges, 2020).

[12] An example of alternative formulation, where technological options are not substitutes, would allow farms selecting which technique to mimic on the basis of such comparison: $\theta^{I}_{it} = \max\{\theta^{IM}_{it}, \theta^{W}_{it}\}$. The resulting equation for the evolution of farm productivity would then become $\theta_{it} = (1-\mu_I)\theta_{it-1} + \mu_I \theta^{I}_{it} + \text{IN}_{it}$.

with $0 < \alpha < 1$, which ensures diminishing returns from labor.[13] As the number of plots of lands are predetermined, without a loss of generality we assume that $S = 1$. Firms owning multiple lands simply collect the output produced by their own properties, thus $Y_{zt} = \sum_{i \in P_{zt}} Y_{it}$, with P_{zt} being the set of farms owned by firm z.

Firms adjust their employment according to the evolution of their demand. In smallholder farming systems, the adjustment operates through either firing or hiring of workers, or through internal migration from urban to rural areas (Rosenzweig et al., 2001; Gollin, 2014). Firms compute their unfilled demand (UD_{zt}):

$$\mathrm{UD}_{zt} = \frac{D_t MS_{zt} - Y_{zt}}{Y_{zt}}, \tag{8}$$

where MS_{zt} is firm's market share and D_t is the total market demand. They then try to learn from their past mistakes, i.e., avoiding over or under-production, by adjusting the number of workers employed in the farms:

$$L_{zt} = L_{zt-1}(1 + \epsilon_L UD_{zt-1}), \tag{9}$$

where ϵ_L is a parameter tuning firms' attitude towards production adjustment. We assume $\epsilon_L < 1$, reflecting a certain degree of stickiness in the labor market, consistently with seasonal labor contracts (Mueller and Chan, 2015). Workers are then allocated to each farm according to the relative productivity of the plots of land:

$$L_{it} = L_{zt} \frac{\theta_{it}}{\theta_{zt}},$$

where θ_{zt} is the average productivity of farms owned by firm z. Each farm has a limit L^{max} to the amount of workers which can operate on it, reflecting again decreasing marginal returns from labor.[14] Firms have to advance wages (w_t) to their workers and they cannot rely on credit, thus they can be financially constraint. In particular, firms have to scale down employment and production if their total wage bill is higher than a fixed share ζ of their current wealth W_{zt}:

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

3.4. The food market

Firms sell food bundles on a centralized market, where they face an exogenous linearly increasing demand, mimicking the observed increase in global population in the last 60 years (Roser et al., 2013), plus a random disturbance:

$$D_t = (D_{t-1} + \Delta^D)(1 + \epsilon_t^D), \tag{10}$$

with $\Delta^D > 1$ and $\epsilon_t^D \sim N(0, \sigma_D)$. We model the market as representative of a stylized food supply chain characterized by monopsony. This setup is fairly representative of small-scale producing contexts, due to the presence of large processing food companies which tend to acquire large quantities of agricultural products from an ensemble of differently sized producing farms. The food price (p_t^{food}) adjusts according to the excess demand $\mathrm{ED}_t = \frac{D_t - Y_t}{Y_t}$[15]:

$$p_t^{food} = p_{t-1}^{food} \left(1 + \epsilon_p \mathrm{ED}_t\right). \tag{11}$$

where ϵ_p is a parameter tuning price sensitivity to imbalances between demand and supply.

After the market price is set, the monopsonistic buyer allocates its demand among firms. Market shares (MS_{zt}) are determined according to the competitiveness of producers via a quasi-replicator dynamics (in line with the evolutionary literature in industrial (see e.g. Dosi et al. 2010, Chiaromonte and Dosi 1993) as well agricultural setting (e.g. Beard and Purcell 2000):

$$MS_{zt} = MS_{zt-1} \left(1 + \epsilon_{MS} \frac{F_{zt} - \bar{F}}{\bar{F}}\right), \tag{12}$$

with $\epsilon_{MS} > 0$. A firm's fitness F_{zt} is given by the inverse of a linear combination of unfilled demand UD_{zt} and firm (inverse) efficiency Υ_{zt}, whose relative weights are governed by the parameters ω_1 and ω_2:

$$F_{zt} = \frac{1}{\omega_1 \Upsilon_{zt} + \omega_2 \mathrm{UD}_{zt,UD>0}}. \tag{13}$$

The fitness measure captures the competitiveness of agricultural firms. First, more productive firm exhibit higher competitiveness in the market thanks, for instance, to the lower production costs they enjoy. We define

$$\Upsilon_{zt} = \frac{1}{Y_{zt}} \sum_{i \in P_{zt}} \Upsilon_{it} Y_{it} \quad \text{with} \quad \Upsilon_{it} = (\theta_{it})^{-1} + \epsilon_{it}^{\Upsilon}, \tag{14}$$

where $\epsilon_{it}^{\Upsilon} \sim N(\mu_t^{\Upsilon}, \sigma^{\Upsilon})$ is a random disturbance capturing small shocks to farm productivity.[16] The firm-level indicator of efficiency Υ_{zt} is simply the weighted average of the indicators of each owned farm, with weights given by the output produced by each farm. As Υ_{zt} enters the fitness at the denominator, higher values of θ_{it} (the main determinant, besides labor, of the volume of output produced by each farm) are associated, ceteris paribus, with larger market shares. Especially in cereal-based markets, large processing food companies tend to favor more productive farms, which can guarantee higher quantities of products at lower costs (Sivramkrishna and Jyotishi, 2008; MacDonald et al., 2018). Thus, by ameliorating the productivity of their farms, agents can increase market shares and the volume of output. Increased productivity dynamically grants a higher competitive advantage, which can in turn stimulate innovation expenditure, leading to self-reinforcing feedbacks. Thus, the model exhibits dynamic increasing return to scale. Second, the UD_{zt} term in Eq. (13) is intended to mimic the idea that firms which are not able to satisfy customers will lose part of them. There are different potential reasons for which firms might not meet their demand, including frictions in labor markets (i.e. inability to quickly adjust labor force when needed) or in the transportation of depletable goods. When firms grow faster, their exposition to such risks increases, as they would need larger adjustment and more transports.[17][18] As we shall see, the coupled dynamics of labor demand

[13] Capital is currently absent from the model. There is no doubt that mechanization has played — and still plays — a role in advancing agricultural productivity (Belton et al., 2021). Nonetheless, in smallholder farming systems, the share of capital in agricultural income is relatively low (labor and land shares of agricultural income typically overcome 60%–70% in developed economies, and they are even larger in developing countries) and capital-related expenditures on total agricultural expenditures fluctuates around 40%, independently of the farming system and prevalent crop type (e.g. Echevarria, 1998; Lowder et al., 2012). In addition, there is evidence suggesting that, in smallholder farming systems, capital is often rented and shared within communities (Diao et al., 2018; Sims and Kienzle, 2017; Mrema et al., 2014). Hence, unless one is interested in studying asymmetric access to physical capital means, we believe our assumption does not alter model's dynamics.

[14] If the resulting labor force in farm i is greater than L^{max}, then the difference is reallocated iteratively among the remaining farms, according to their re-computed relative productivities. It follows that $L_{zt} \leq \#(P_{zt})L^{max}$, where $\#(P_{zt})$ is the cardinality of the set P_{zt}, i.e. simply the number of farms owned.

[15] Since we do not model explicitly new waves of innovations, no technological agricultural treadmill hypothesis (Cochrane, 1958) is considered.

[16] 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}. Thus $\mu_t^{\Upsilon} = \mu_{t-1}^{\Upsilon}(1 + \Delta_t^{\theta})$.

[17] Frictions can be substantial in marginal rural markets of developing contexts (Cook and Cook, 1990; Roberts et al., 2017; Thacker et al., 2019). For instance, inefficient transport infrastructures hinder the competitiveness of producers and the development of rural areas (for a recent case study, see Prus and Sikora 2021, Bacior and Prus 2018).

[18] In the model, one of the effects of these frictions is to tame increasing market concentration. Even if diminishing the influence of ω_2 (or even removing

and market share adjustments balances under/overproduction making our artificial economy gravitating around the zero-waste level of output (excess supply equal to zero on average), with errors reflecting imperfect information and agents' bounded rationality.[19]

3.5. Profits and land re-allocation

At the farm level, profits (Π) are simply the difference between revenues and total costs:

$$\Pi_{it} = S_{it} p_{it}^{food} - w_t L_{it} - r_{it}^{\ell}, \tag{15}$$

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

$$r_{it}^{\ell} = r_t^{\ell}(1 + \epsilon_{it}^{r}). \tag{16}$$

This modeling decision approximates the complex determinants behind land price establishment (Hallam et al., 1992).[20] At the firm level, profits are computed summing the profits of all owned farms:

$$\Pi_{zt} = \sum_{i \in P_{zt}} \Pi_{it}. \tag{17}$$

The dynamics of profits affect the evolution of the stock of liquid assets ($W_z t$) of the firms:

$$W_{zt} = W_{zt-1} + \Pi_{zt}. \tag{18}$$

Firms with negative wealth go bankrupt and their farms go on sale. Other firms can acquire the land through a second-best auction mechanism. Two factors drive the decision to place a bid: (i) the spatial proximity of the farm to be sold with respect to those owned by the bidder; (ii) the demand pressure experienced by the bidder, measured by the average unfilled demand in the last s^u periods. Formally,

$$\text{Prob}(\text{BID}_{zt} = 1) = I_{zt} exp(-\epsilon^A d_{ij}) \quad \text{with} \quad I_{zt} = \begin{cases} 1 & \text{if} \quad \sum_{h=t-s^u}^{t} UD_{zh} > 0 \\ 0 & \text{if} \quad \sum_{h=t-s^u}^{t} UD_{zh} \leq 0 \end{cases} \tag{19}$$

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 $B_{zt} = \Xi W_z t$. The N bids are then ranked from the highest to the lowest $B^1 \dots B^N$. The firm placing the highest bid B^1 obtains the ownership of farm j, paying a price equal to B^2.[21]

After the auctions, some plots of land can be unsold. We consider two scenarios. In the first one, we assume that farms that are not acquired by any agent are simply assigned to new entrant firms which are random copies of incumbents. In the second setting, unsold farms are abandoned, and the soil upon which they operated then turn into forests after T^f periods (cf. Section 3.6.1; Gellrich et al., 2007). This process mimics the abandonment of lands due to spatial isolation, low level of soil productivity and/or insufficient demand pressure (Haddaway et al., 2014), observed in smallholder farming contexts (Mather, 2007).

3.6. Additional modules

The model is designed to be a flexible tool to explore the impacts of different environmental and climate scenarios on the agricultural sector. In this Section, we describe three additional modules which can be activated to test the model in distinct applications, namely deforestation and land abandonment (Section 3.6.1), conventional vis-á-vis sustainable agriculture (cf. Section 3.6.2), and climate-change impacts (see Section 3.6.3).

3.6.1. Deforestation and reforestation dynamics

The initial number of forests dislocated across the grid evolves dynamically through *deforestation* and *reforestation* processes. The latter takes place in abandoned plots of land as explained in Section 3.5. Conversely, deforestation takes place when increasing demand for food generates pressure for the exploitation of virgin land available for crop production, as observed e.g. in Brazil (Andersen et al., 2002) and other fast-growing economies. More formally, at each t the probability of a firm to deforest a spatially close forest (i.e. within a given distance d^f from one of his farms) is given by

$$\text{Prob(Deforesting)} = 1 - exp(-\epsilon_f \frac{1}{s^u} \sum_{h=t-s^u}^{t} UD_{zh}), \tag{20}$$

where ϵ_f is a parameter tuning the propensity to deforest. Thus, the higher the unfilled demand UD experienced in the last s periods by firm z, the higher the probability to deforest. Note that only firms engaged in intensive agriculture (cf. Section 3.6.2) can undertake deforestation actions. The farm productivity on new arable land is equal to that of the conventional farm which undertook the deforestation action,[22] plus a fixed proportion Δ^f reflecting a productivity gain resulting from the usage of a virgin land (Barbier et al., 2010). Each farm belonging to the deforesting firm contributes (proportionally to its net worth) to endow the newly created farm with some initial wealth, representing set-up costs, e.g. investments in infrastructure for sowing, ploughing and harvesting on a newly arable land (Barbier and Burgess, 1997).

3.6.2. Conventional versus sustainable agricultural regime

We further explore the model to provide insights on the transition of agriculture into an environmentally sustainable regime. A first battery of results is presented in Section 4.3.2, as the detailed exploration of this module will be the object of a forthcoming study. We envisage the existence of two agricultural technological regimes, representative of two different set of techniques and processes: *conventional* agricultural regime vs. *sustainable* one (Saifi and Drake, 2008). We stem from the fact that technological change and innovations in the agricultural sector typically have a twofold effect: they can boost productivity and increase food availability, but, at the same time, they can hinder environmental sustainability and climate change resilience (Tilman et al., 2011; Roy et al., 2016).

Conventional farming techniques, usually characterized by intensive cropping and landscape homogenization (Schrama et al., 2018), grant an increase in agricultural yield (Robertson et al., 2014), but they lead to consistent losses in terms of soil organic matter and soil biodiversity (FAO, 2013). Firms performing a conventional type of agriculture do not succeed in re-integrating completely the soil nutrients and

it, by setting $\omega_1 = 1$, which implies $\omega_2 = 0$, see Table B.1) results in a higher level of market concentration, its qualitative evolution remains unchanged (see Fig. D.2).

[19] Firms get a fraction of demand corresponding to its market shares. The possible residual demand is allocated to firms which produced more than they were assigned, by re-weighting market shares accordingly. If there is still unsatisfied demand, the process iterates until total assigned sales are equal to the minimum between total demand and total supply, i.e. $\min\{D_t, Y_t\}$.

[20] Admittedly, we do not model dynamics of land rental market, a relatively common phenomenon in smallholder farm settings.

[21] Consistently with our definition of farm productivity, assume that the acquired farm carries with it all the factors contributing to its productivity, thereby including not only soil characteristics, but also, the entire set of capabilities, skills and inputs employed in the productive process.

[22] We thereby assume that the latter transfer to the newly born farm all its productive technology, beside sharing its wealth with it.

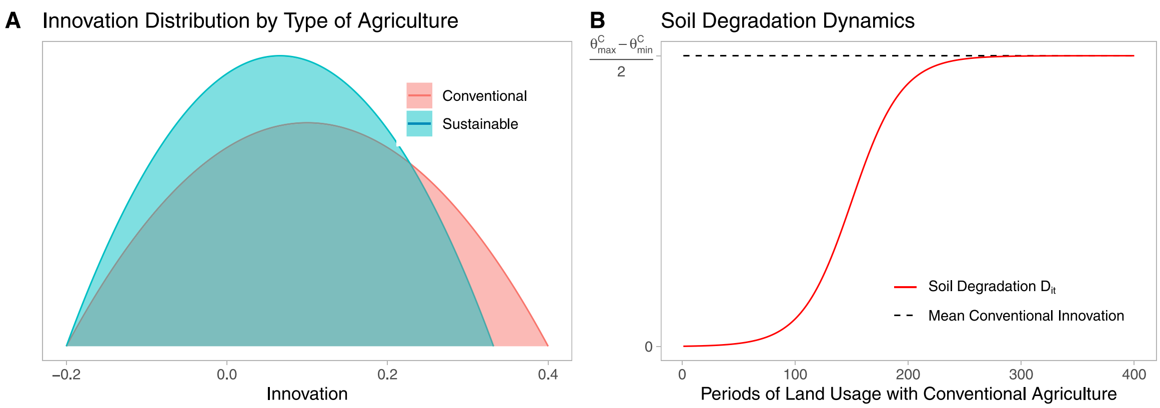

Fig. 3. Soil productivity dynamics in different agricultural regimes. Panel A: different innovation supports for conventional and sustainable farming. Panel B: graphic representation of soil degradation mechanism.

carbon (Mazzoncini et al., 2010; Vitousek et al., 2009), causing a long-run impoverishment of soil fertility and eventually to a slowdown, a stagnation or even a fall in yields (Ray et al., 2012; Borrelli et al., 2017).

Sustainable farming techniques (Rockström et al., 2017) are typically based on increasing organic matter supplies to soils, thus granting the preservation of soil nutrients. In that, they are a viable alternative solution to agricultural intensification (Schrama et al., 2018). Although sustainable farming is recognized as a promising alternative (Robertson et al., 2014), yields are usually reported to lag behind those of conventional farming (Ponisio et al., 2015; McKenzie and Williams, 2015; Barbieri et al., 2021).

We model the differences between intensive and sustainable farming, assuming that conventional farms exhibit a higher innovation potential, i.e. a larger support from which they actually draw gains in productivity when innovating (see Fig. 3A), but they lead to long-run soil depletion. We here focus only on human-induced soil depletion (Oldeman et al., 2017), a type of degradation intimately connected with the intensity of agricultural activities.[23] On the contrary, sustainable farms preserve the soil nutrients, but their productivity is lower. Soil degradation impacts negatively on farm productivity through the term SD_{it}. Therefore, Eq. (6) now becomes:

$$\theta_{it} = (1 - \mu_{IM} - \mu_W)\theta_{it-1} + \mu_{IM}\theta^{IM}_{it} + \mu_W\theta^{W}_{it} + \text{IN}_{it} - \text{SD}_{it}, \quad (21)$$

where μ_{IM} and μ_W are analogous parameter to μ_I in Eq. (6). We assume that SD_{it} depends on the number of time periods T^c_{it} in which the farm i has been producing in a conventional regime, and evolves according to a logistic function:

$$\text{D}_{it} = A + \frac{K - A}{1 + e^{-b(T^c_i - M)}} \quad (22)$$

where b controls the growth rate, M shifts the logistic on the horizontal dimension, A tunes the lower asymptote (in our case, clearly equal to 0), and K the upper asymptote (Fig. 3B).[24] The flexibility of the logistic specification allow us to experiment with different scenarios of soil depletion originated by land-use change, due e.g., to heterogeneous scale and spatial effects.[25]

Firms choose between intensive and sustainable farming through a discrete choice model (Brock and Hommes, 1997). Hence, once the farming regime changes, all farms owned by the firm switch accordingly. Each firm z compares the output of farms employing conventional techniques C_{zt} with those using sustainable ones S_{zt}, within a certain ray of observation d^s (Section 3.2).

$$\gamma^S_{zt} = \frac{exp\left(\tau \cdot \frac{1}{\#(S_{zt})}\frac{1}{m}\sum^{i \in S_{zt}}_{k \in [t-m,t]} \frac{Y_{ik}}{L_{ik}}\right)}{Z_{zt}} \quad (23)$$

$$\gamma^C_{zt} = \frac{exp\left(\tau \cdot \frac{1}{\#(C_{zt})}\frac{1}{m}\sum^{i \in C_{zt}}_{k \in [t-m,t]} \frac{Y_{ik}}{L_{ik}}\right)}{Z_{zt}} \quad (24)$$

with Z_{zt} being the sum of the two numerators. The quantities between parenthesis are just the average output per worker produced in the last m periods by neighboring sustainable and conventional farms, multiplied by a parameter τ governing the intensity of switching. Firms are allowed to switch only every q periods. A firm of type will thus C attempts to switch only if the amount produced by the observed set of farms employing sustainable techniques is higher than that produced by the observed set of farms employing conventional techniques. Thus, it will attempt to switch only if $\gamma^S_{zt} > \gamma^C_{zt}$, and actual switching is decided through a Bernoulli trial with mean γ^S_{zt}. The converse holds true for firms of type S. Finally, imitation is allowed only within farms employing the same agricultural technique (resembling the concept of technological proximity, see Pomp and Burger 1995).

3.6.3. Climate shocks

The literature studying the impact of climate change on agriculture is large and well-developed, both at the empirical level and in terms of modeling (Nelson et al., 2009, 2014). Here we adopt a parsimonious framework to study how exogenous climate-related shocks can affect the dynamics of food production, food price and land productivity in the model.

Agricultural output is highly dependent on weather conditions (Lobell et al., 2008; Lobell and Field, 2007). Extreme weather events, whose economic impact are on the rise (see e.g., Coronese et al., 2019), can drastically reduce yields and have long-lasting effects on farms productivity (Lobell et al., 2011). We assume that a climate-related shock (e.g. a flood, an extreme heat wave, or a variation in precipitations) hits the farm i at time t, destroying a fraction λ_{it} of the current period harvest. Formally, given the output produced without the effect of weather-related events $Y^*_{it} = \theta_{it}L^{\alpha}_{it}$, the actual crop harvested after

[23] Other forms of soil erosion caused by natural hazards (like high winds and drought conditions in dry areas) can be instead qualitatively assimilated — in the context of this model — to climate shocks, i.e., random disturbances which lower output and overall productivity (see Section 3.6.3).

[24] To be conservative, we assume that loss 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 SD_{it}).

[25] As shown in Fig. 3B, we typically parametrize the logistic function in a way that allows us to replicate empirical dynamics of stagnating agricultural yields (Ray et al., 2012); the maximum loss is indeed set equal to the mean innovation for conventional farmers, potentially implying a plateau in farm productivity.

the impact is:

$$Y_{it} = \lambda_{it} Y^{*}_{it}, \tag{25}$$

where the shock λ_{it} is extracted from a truncated normal distribution, i.e. $\lambda \sim N(\bar{\lambda}, \sigma_{\lambda})$ with $\lambda_{min} = 0$ and $\lambda_{max} = 1$. Letting the parameters of the distribution evolving over time, one could mimic the effects of climate change (Lamperti et al., 2018, 2019a). To account for spatial correlation, we assume that the shock propagates to surrounding farm j, and the effects decays with the distance d_{ij} between the origin of the event i and the neighboring farm j, according to:

$$\lambda_{jt} = exp(-\epsilon_{\lambda} d_{ij}) \lambda_{it}, \tag{26}$$

where ϵ_{λ} is a parameter tuning the spatial rate of decaying of extreme events intensity.

3.7. Model setting, parameterization and simulation setup

As typical within ABM models, non-linearities arising from the complex interactions of boundedly rational agents impede analytical closed-form solutions (Fagiolo et al., 2019). We thus study the model through extensive numerical simulations. Between-simulations variability (due to stochastic terms and path dependence) is taken into account through Monte Carlo replications. Results are then presented in the form of Monte Carlo averages (with relative standard errors), although representative single runs are sometime shown to illustrate a prototypical behavior.[26]

The model is initialized and parameterized to match realistic shares and dynamics attributable to smallholder farming systems. A typical run consists of 400 periods, after a "warm-up" phase of 100 periods required to remove transient dynamics. Relevantly, we emphasize that our simulations do not attempt at mirroring any particular region or country; rather, we aim to show the emergence of agricultural production regimes in a theoretical yet realistic set of scenarios, independently of local specificities.

We adopt the following procedure to initialize the model after the transient. The percentage of cells starting as forests is 20%, in line with empirical evidence at the global level (Sanchez et al., 2009). The simulation begins with one firm per arable land plot, with growing land concentration arising endogenously. In terms of spatial configuration, our baseline specification has forestry clustered at the center of the grid, while initial land productivities are spatially randomized. When including different agricultural regimes, the model starts with 25% of sustainable farms and 75% of conventional ones, relying on global estimates on the diffusion of organic agriculture.[27] Estimates for productivity differentials between sustainable and conventional farming are quite variable and location-specific. For this reason, we conservatively choose a large gap between the two by assuming that conventional farming is initially 30% more productive than sustainable one. In addition, reliable estimates on the different innovation potential — the support of the distributions from which innovation are drawn — between the two agricultural regimes are even harder to find. Thus, we choose a relatively high differential (17%) consistent with a conservative scenario. These assumptions make the diffusion of sustainable agriculture relatively more difficult.

For what concerns the choice of parameters' values, our simulation strategy follows a procedure akin to an indirect calibration approach (Fagiolo et al., 2019). We start by directly calibrating parameters for which some robust empirical evidence across smallholder farming system exist. Accordingly, we set: $\alpha = 0.8$, as reflecting a relatively low capital share of agricultural income (Hertel et al., 2020; Echevarria, 1998); $\epsilon_L = 0.3$, proxying low employment elasticity and relatively rigid agricultural labor markets (Islam and Nazara, 2000; Rosenzweig, 1988; Ramoni-Perazzi and Orlandoni-Merli, 2019); $\epsilon_P = 2\%$, in line with recent empirical evidence (Zelingher et al., 2021); and, finally, $r^{IN} = 0.1$ and $r^{IM} = 0.05$ are broadly consistent with the figures of expenditures for innovation purposes on total sales of agricultural firms in a variety of countries (Pray et al., 2015). Second, we explore the parameter space in order to reproduce a set of real-world-based empirical regularities, such as trends in aggregate production (Gebremedhin and Christy, 1996), employment (Mueller and Chan, 2015), market concentration (Vickner and Davies, 2000), food price (Christian and Rashad, 2009), and distribution of land ownership (Wegerif and Guereña, 2020), selecting the configuration allowing to match such features. The list of baseline parameter values is reported in Table B.1, while the details of the baseline model initialization are given in Table B.2.

4. Results

We perform a battery of simulation exercises to study the results generated by the model under different configurations and scenarios. We start with a *plain-vanilla* version of the model (Section 4.1), where: (i) we do not allow for deforestation and land abandonment, (ii) we do not account for human-induced soil depletion, (iii) there is no distinction between conventional and sustainable farming and (iv) climate shocks are absent. We then explore the effects of some key parameters (Section 4.2). Finally, we gradually add features to showcase the flexibility of the model and the effects of a variety of elements on the dynamics of food production. In particular, we consider deforestation and land abandonment (Section 4.3.1), human-induced soil degradation and sustainable farming (Section 4.3.2), and climate shocks (Section 4.3.3).

4.1. The Plain Vanilla model

The model replicates a pool of micro and macro stylized facts of the agricultural sector in countries dominated by a smallholder farming system. The baseline scenario (not encompassing any type of environmental boundary) stylizes in fact a healthy economy, as summarized in Fig. 4 and Table 1. The model generates a linear growth in total output (Fig. 4A), as observed in real-world data for cereal production (Fig. 4J). Such increase has been in turn driven by an analogous growth in yields (Fig. 4K). Indeed, farm productivity in the model (shown in Fig. 4H at the micro/farm level) evolves, on average, in a linear way. Food price slightly decreases over time (Fig. 4C). The growth in output is coupled with a secular decrease of employment in the agricultural sector (Fig. 4A). This result matches a long-lasting trend observed in real-world data (Mueller and Chan, 2015), as labor force have progressively left — with different magnitudes across the globe — the primary sector (Fig. 4L). This aggregated trend hides nonetheless a remarkable heterogeneity at the farm level (Fig. 4G), with single farms experiencing periods of rising employment, in the attempt to fulfill the demand they face and expand their market shares. Both rising output and the declining trend in labor are entirely due to increases in productivity (Adamopoulos and Restuccia, 2019).

Heterogeneity among farms tends to evolve over time. Initial productivity, while giving a remarkable competitive advantage (mostly via path-dependence, see Table 1 which documents a correlation of 0.72 between initial and final farm productivity), represents no guarantee of success over time (Adamopoulos and Restuccia, 2019). Innovation and imitation activities are affected by the ability of the firm to generate revenues, which in turns stems from the complex interactions between farms and the institutional setting in which they operate (Alston and

[26] We notice that the Monte Carlo distribution of the statistics of interest are always single peaked, which support the idea that the baseline model produces ergodic dynamics (Vandin et al., 2022).

[27] As the definition of sustainable farming in this work is broader than organic farming alone, we adopt the least conservative estimate among those proposed for enumerating the share of sustainable farms.

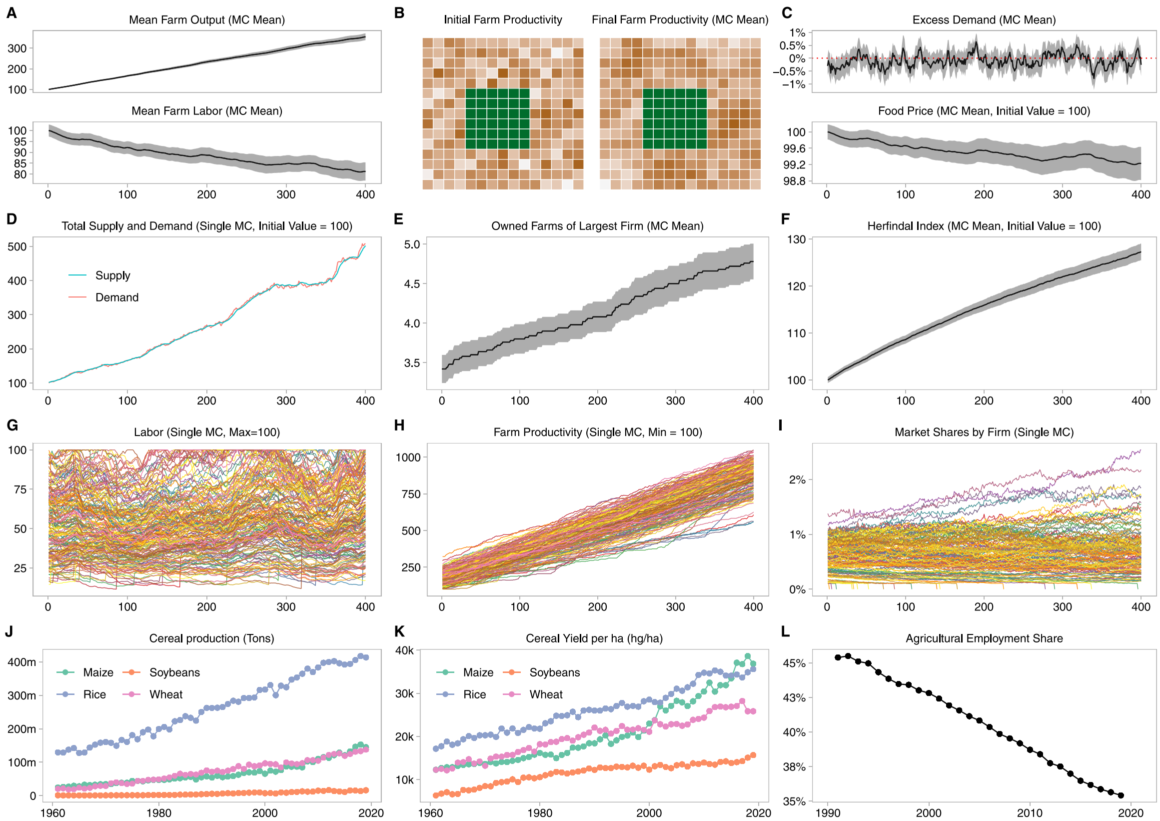

Fig. 4. Panel A to I: Baseline model results. Horizontal axis showing time steps. 50 Monte Carlo replications. Shaded areas are 95% confidence bands. Panels J to L: Long-run evolution of agricultural output, yield and employment in countries characterized by small-holder farming settings (below the median of the global distribution of countries' average farm size, i.e. under 4.9 ha per farm). Horizontal axis showing years. Agricultural employment expressed as percentage of total employment.
Sources: Data on average farm size per country from Lowder et al. (2021); data on cereal production and yield (panels J and K) from FAOstat; data on agricultural employment (panel L) from World Bank.

Table 1
Summary statistics for baseline model.

	Excess demand (%)	Food price (% Initial-final change)	Bankrupts (% of initial firms)	Mean output growth (%)	Land productivity (Initial final correlation)
MC Mean	−0.1	−0.78	11.35	0.32	0.72
MC SE	*(0.02)*	*(0.2)*	*(0.32)*	*(0.01)*	*(<0.01)*

Note: 50 Monte Carlo replications. Monte Carlo standard errors between parenthesis.

Pardey, 2020). Fig. 4B highlights the importance of initial soil productivity, while stressing the emergence of locally clustered areas of higher farm productivity driven by local interactions (see Sections 4.2.1 and 4.2.2). Indeed, a certain number of takeovers is observed even at the productivity frontier (Fig. 4H). Market dynamics are more evident when looking at firm market shares (Fig. 4I), which show persistent fluctuations, due both to market performances and acquisition of defaulted farms. The activity of expansion carried out by firms gives rise to an increasing concentration of land (Fig. 4E), in line with the empirical evidence (Vickner and Davies, 2000). These dynamics, coupled with positive feedbacks between innovation, land productivity and market shares, generates an increasing Herfindahl Index (Fig. 4F), testifying a growing market concentration (Howard, 2009). The system is able, on average, to serve the demand for food, despite short-run fluctuations stemming from micro-level shocks and coordination failures (Fig. 4C). The economy produces on average slightly more food than the amount demanded. This is reflected by a slightly decreasing price of food (Table 1), as observed in the data (Alston, 2000). Finally, comparing Table C.1 to Table 1 shows that drastically increasing the number of Monte Carlo replications (from 50 to 500) do not alter model results, but only entails a small reduction in standard errors.

4.2. The baseline configuration and its dynamic unfolding

4.2.1. Learning and selection

The diffusion of knowledge spillovers is crucial in agriculture (Evenson, 2000; Clancy et al., 2020). Such process is heavily affected by geographical closeness, both through imitation and within-firm learning activities, (Section 3.2), as acquisitions of farms are more likely to happen among neighboring farms (Eq. (19)). In this Section, we explore the role of these mechanisms. More precisely, we turn on and off innovation and within-firm learning at three different values of replicator dynamics intensity ϵ_{MS}, which captures different strengths of market selection.

Learning mechanisms appear essential to influence both the mean and the dispersion of farm productivity in the model (Fig. 5A and Table C.5), although in a different fashion. Imitation reduces farm productivity variance, but its primary role is to remarkably rightward shift the farm productivity distribution by accelerating technological diffusion. This is in accordance with established dynamics of technological imitation among food producers, where highly accessible technical advances are crucial to spur productivity especially for smaller actors (Ugochukwu and Phillips, 2018). The positive effect of within-firm

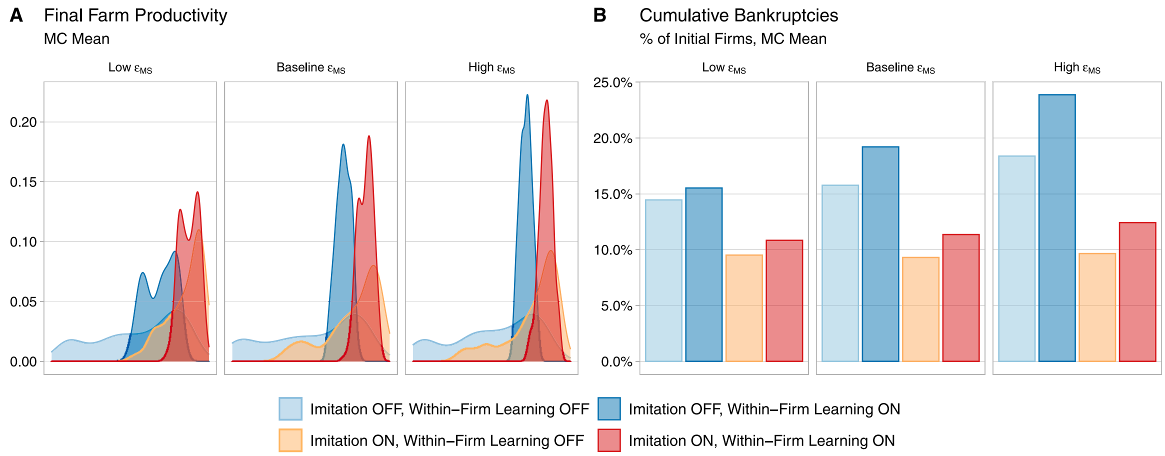

Fig. 5. Farm productivity and bankruptcies for different levels of imitation, within-firm learning and replicator dynamics intensity (ϵ_{MS} values: low $\epsilon_{MS} = 0.2$, baseline $\epsilon_{MS} = 0.5$, high $\epsilon_{MS} = 0.8$). 50 Monte Carlo replications. See Table C.5 for further details and significance tests.

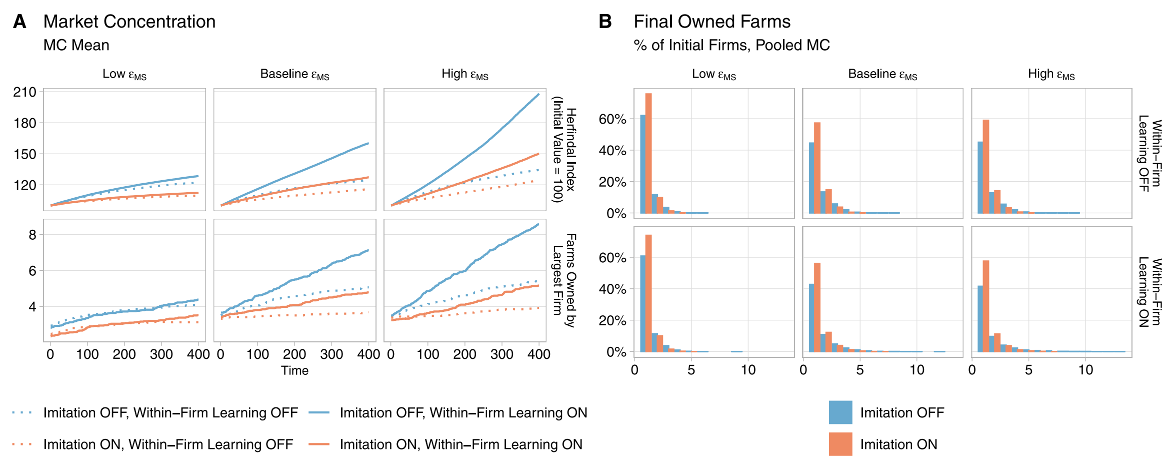

Fig. 6. Market and land concentration for different levels of imitation, within-firm learning and replicator dynamics intensity (ϵ_{MS} values: low $\epsilon_{MS} = 0.2$, baseline $\epsilon_{MS} = 0.5$, high $\epsilon_{MS} = 0.8$). 50 Monte Carlo replications. See Table C.5 for further details and significance tests.

learning on mean farm productivity is statistically significant, but milder with respect to imitation (Table C.5). On the other hand, it reduces farm productivity dispersion more effectively. As a matter of fact, smaller and impoverished farm actively benefit from being acquired by larger and more productive firms, which transfer their knowledge (Fuglie et al., 2012).

How does market selection interact with these two learning channels? Within-firm leaning becomes more effective when market selection is stronger (Fig. 5A), as the number of farms acquisitions increases (Fig. 5B). Within-firm learning has thus a twofold nature: on one side, it favors knowledge spillovers reducing productivity dispersion. On the other side, it boost large firms market shares, further augmenting bankruptcies. This effect becomes evident with higher replicator dynamic intensity values. On the contrary, the productivity boost granted by imitation activities effectively reduces the number of bankruptcies, in line with the literature which identifies in the lack of technology adoption and imitation a crucial influencing factor for farm failures (Shepard and Collins, 1982).

Indeed, while imitation diminishes the Herfindahl index, within-firm learning has the opposite effect (Fig. 6A). These findings substantiate the idea that the existence of reinforcing mechanisms, driven by the secretive nature of within-firm learning, can help the creation of clusters of oligopolistic producers. Moreover, both mechanisms shape the distribution of owned farms (Fig. 6B). Land distribution in the baseline model is highly rightward skewed, with very few firms owning a large number of farms, in line with recent empirical evidence on farm size (Wegerif and Guereña, 2020). Such skewness appears to be less marked in presence of imitation activities, while within-firm learning exacerbates it.

Finally, if imitation and within-firm learning are absent, the system results impaired in fulfilling the food demand (Table C.5), thus resulting in a scenario with positive average excess demand and a slightly increasing price. Technological change has a fundamental role in the agriculture sector to spur crop production in order to feed an increasingly populated world. In Appendices C and D, we explore the robustness of these findings by varying intensity of both imitation and within-firm learning effects (i.e. μ_{IM} and μ_W). The results (Fig. D.1 and Table C.9) document dynamics which are in line with those described above.

4.2.2. Spatial distribution and productivity

We here explore how different initial spatial configurations of soil productivity affect the dynamics of the model. We consider four spatial scenarios (cf. Fig. 7), ranging from randomized productivity distribution (our baseline specification) to the most extreme polarized case of two clusters encompassing high and low productivity plots. The mean initial productivity of the system is kept constant across scenarios,

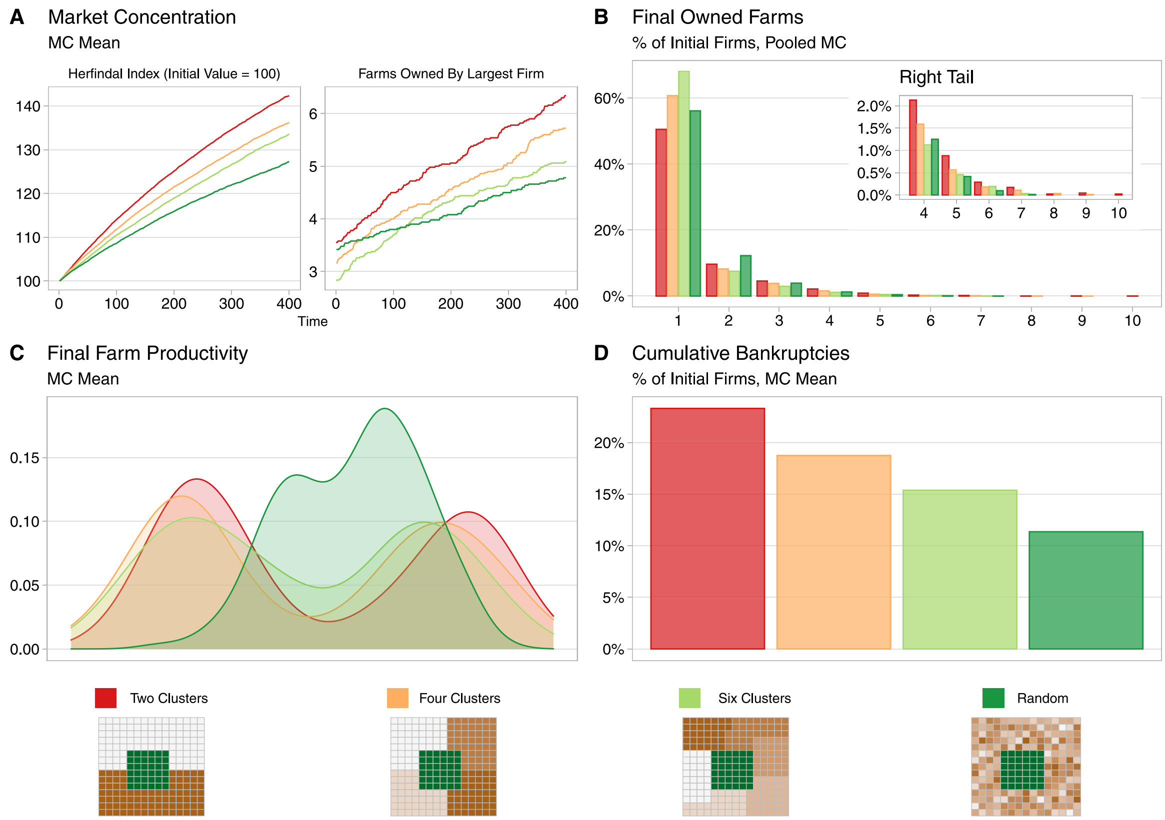

Fig. 7. Results for different spatial scenarios of initial land productivity. 50 Monte Carlo replications. See Table C.2 for further details and significance tests.

while its variance changes as more or less productive cells are increasingly clustered. Designing productivity clusters entails the creation of a spatial grid more akin to actual agricultural ecosystems (Msanya et al., 2003). For example, there is little doubt that temperate pedo-climatic areas soils are more prone to agricultural activities given climate and irrigation configurations (Eswaran et al., 1997).

Productivity clustering appears to be quite detrimental to the economy's performances: higher segregation results in higher market and farm concentration (Fig. 7A), a more skewed distribution of firm size (Fig. 7B) and a higher number of bankruptcies (Fig. 7D), without decreasing food price (Table C.2). When less productive farms are clustered together, their ability to benefit from local imitation is seriously hampered, as well as their chances to be acquired from bigger firms and enjoy the benefits arising from knowledge spillovers. The puny performance of low-productivity farms is not entirely counterbalanced by the advantages of clustering together more productive cells: Table C.2 documents significantly lower mean productivity in segregated scenarios, as well as higher variance. The importance of local interactions is well evident in Fig. 7C: the two-cluster scenario results in fact into a marked bi-modal distribution of land productivity, compared to the randomized case where bi-modality is almost absent. Interestingly, also intermediate scenarios (four and six clusters) generate almost identical bi-modalities, suggesting that a small amount of initial segregation is likely to generate persistent and self-reinforcing inequality in absence of governmental policies.

Our findings reflect current views on the inefficiencies arising from productivity clustering, which rarely compensate at the aggregate level (Anríquez and Bonomi, 2007). Dynamics observed in Sub-Saharan smallholder contexts exemplify this idea: more fertile areas tend to be extensively exploited, while other regions lag behind and in most cases are still representative of ancestral techniques (e.g. ox-plough technologies), inevitably reducing the overall efficiency of the system, both in terms of yield and development strategies (Ruttan, 2002).

4.3. Applications

4.3.1. Deforestation and land abandonment

In this Section we allow for deforestation and reforestation, as defined in Section 3.6.1, and we study the ensuing dynamics. Deforestation activity, through the establishment of newly born farms by already existing firms increases land concentration, an effect which in turn causes also an upsurge in market concentration (Fig. 8A). This translates in a more skewed distribution of firm sizes (Fig. 8D). The benefits enjoyed by largest firms, as well as the advantages deriving from the usage of highly productive virgin areas, further penalizes smaller firms, resulting in a more right-skewed distribution of land productivity (Fig. 8C). On the other hand, mean productivity is significantly lower, albeit the size of the effect is small (Table C.3).

Most importantly, in absence of any policy for forest protection, forests tend to decrease over time: up to 60% of forest are lost at the end of the simulation in our benchmark scenario (Fig. 8B). Despite no change in institutional settings with respect to baseline model (e.g. market intensity, demand pressure), the system leads to depletion of limited natural resources even in absence of food scarcity issues, as shown in Table C.3 (Goers et al., 2012). Thus, net exploitation of forests is driven not by the global need for more arable land to satisfy increasingly high levels of food demand, but rather from unilateral incentives of firms which try to boost their production and profits. Indeed, firms which are not able to fulfill their demand with the current level of production, resort to deforestation in the attempt to increase their market shares (Kanninen et al., 2007), as in the emblematic the cases of the Amazon and Kenyan forests (Viana et al., 2016; Njeru, 2013).

Finally, we perform robustness checks over the parameter T^f, which regulates the time needed for an abandoned land to be reconverted into a virgin land. As shown in Fig. D.3 Table C.7, the stock of remaining forests at the end of the simulation does not vary significantly across

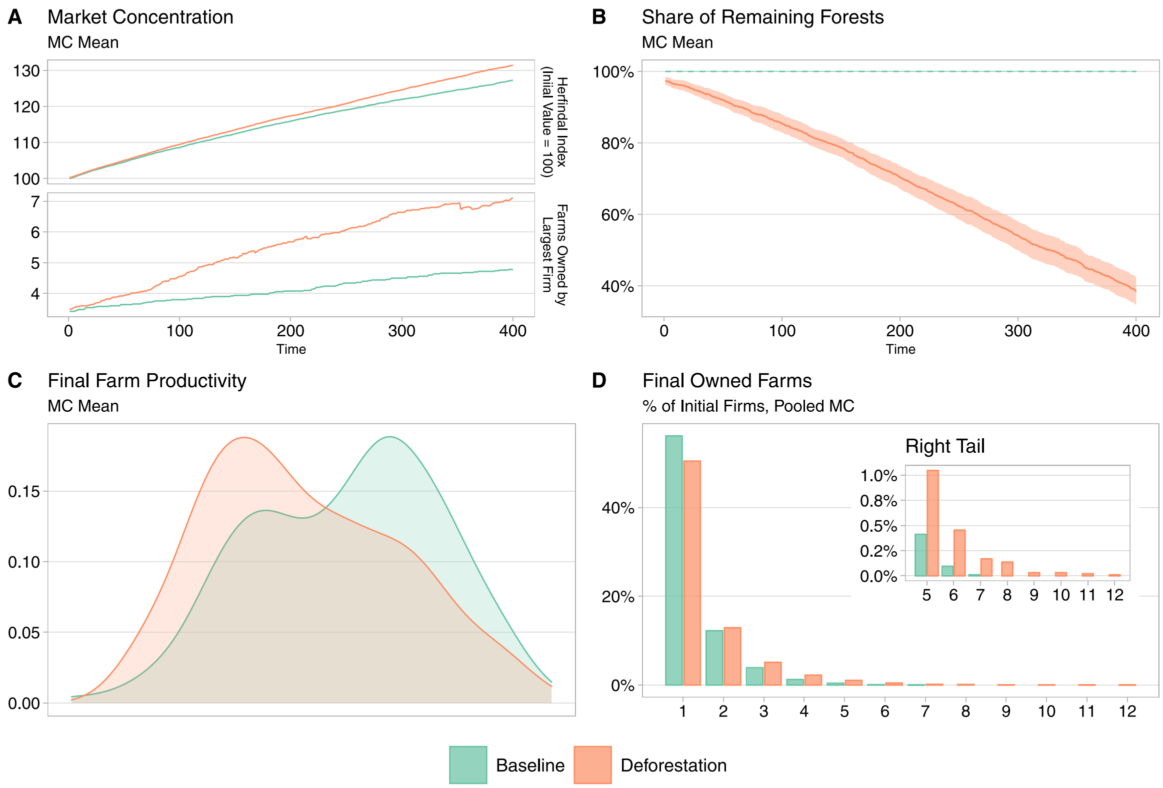

Fig. 8. Results with deforestation and land abandonment, and without (baseline). 50 Monte Carlo replications. Shaded areas are 95% confidence bands. See Table C.3 for further details and significance tests.

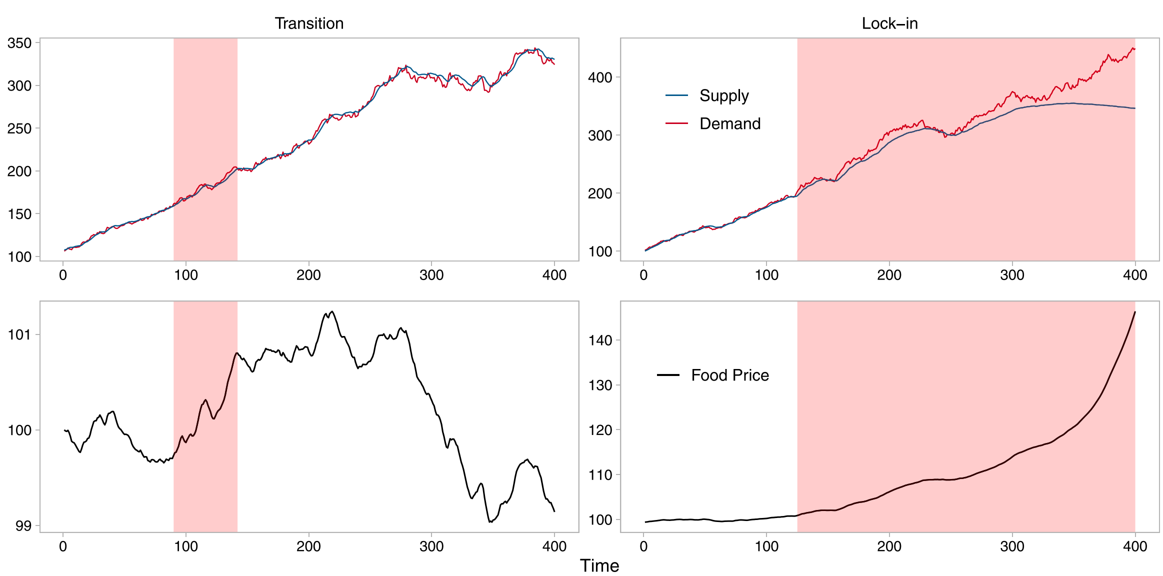

Fig. 9. Transition and lock-in scenarios in the model. Two different single runs of the model, exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming and conventional lock-in. For each run, distance between total demand and supply and food price dynamic are shown. Red areas correspond to periods of insufficient food supply.

different values of T^f. As a matter of fact, the model is simulated under demand scenarios which impose a fairly high pressure on land use; as a result, plots of land being left unpurchased (and later turned into forests) are a relatively rare occasion (Table C.7).

4.3.2. Human-induced soil degradation

We investigate transition dynamics when allowing for heterogeneous agricultural techniques (conventional vis-á-vis sustainable) and human-induced soil degradation (Section 3.6.2). Agents infer the soil depletion rate implied by their technological choices by observing their output, as well as those of their neighbors. In a typical run, conventional farming will be more productive in the early stages of the simulations due to higher innovation potential. Surging human-induced soil degradation due to soil management malpractices reduces the productivity of intensive production techniques, possibly triggering the transition towards sustainable farming.

Fig. 9 shows two runs exemplifying the limiting cases the model is able to generate. In the first scenario, sustainable farming spread

Table 2
Transition, lock-in and intermediate cases probabilities using both output per worker and output as performance proxy, and summary statistics with and without human-induced soil degradation.

	Transition dynamics			**Macro variables** (t = 400)	
	Lockin probability	Transition probability	Intermediate cases	Excess demand (%)	Remaining forests (%)
Soil Degradation ON	78%	16%	6%	11.88*** *(1.87)*	12.33*** *(3.24)*
Soil Degradation OFF	100%	0%	0%	0.11 *(0.17)*	41.11 *(1.83)*

Note: Transition probability is defined as the share of Monte Carlo runs with final share of sustainable farms greater than 90%, lock-in probability as the share of runs with final share of sustainable farms equal to 0. Monte Carlo standard errors within parenthesis. p-values significance codes for T-test for mean difference with respect to "Soil Degradation OFF" scenario (independent samples, unequal variances): *** ≤ 0.001, ** ≤ 0.01, * ≤ 0.05, . ≤ 0.1.

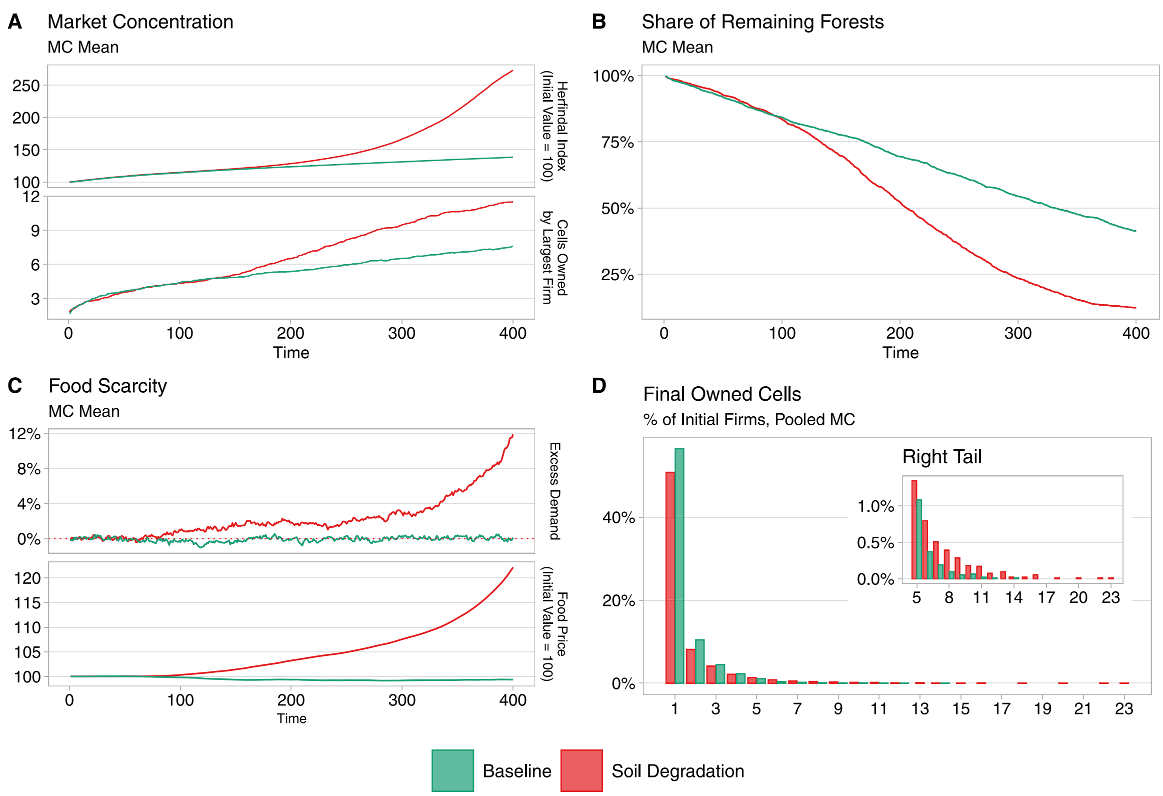

Fig. 10. Results with human-induced soil degradation and without. 50 Monte Carlo replications. As soil degradation and regime switching introduce a source of non-ergodicity in the model, in order to keep the location of sustainable/conventional farms constant during the transient, we suspend auctions and deforestation activities during the transient itself (defaulted farms are substituted by random copies of incumbents, as explained in Section 3.5). For the same reason, switching is allowed only after the transient. See Table C.4 for further details and significance tests.

gradually in the lattice as the first signs of human-induced soil degradation (increasing excess demand, rising price of food) become evident to agents, thus causing a rapid *transition* to the sustainable regime. In this case (left quadrants of Fig. 9), food supply keeps the pace of food demand, and shortages are almost absent, as shown by the small and temporary increase in food price. However, several circumstances can delay or prevent sustainable transition. If the competitive advantage initially gained by conventional firms is too high, all firms will switch to a conventional regime without considering future losses associated with increased human-induced soil depletion, resulting in a *lock-in* scenario (right quadrants of Fig. 9). Losses from human-induced soil degradation accumulate, slowing down farm productivity growth. Agents react by hiring more workers, acquiring new land and deforesting virgin areas until soil productivity binds and food production reaches a plateau. Because of increasing food demand, this scenario implies a persistent increase in food scarcity and price. Surging food prices in presence of human-induced soil degradation have been abundantly documented for different types of crops (Lal, 2004).

Comparing the dynamics of the model with human-induced soil degradation against the baseline scenario provides further insights. In presence of human-induced soil degradation, without any policy supporting sustainable transition, the probability of lock-in is very high (78%, Table 2), coherently with recent studies (Jaime et al., 2016). In the baseline scenario with no soil depletion, the system obviously always converge to intensive farming, which is the most productive technique. With human-induced soil degradation, the inability to switch to a sustainable regime (because of coordination failures, misaligned incentives and imperfect information) results in a persistent and growing scarcity of food, which translates into a growing food price (Fig. 10C).[28] Due to stagnating (or even descending) levels of farm productivity, several firms lose market shares and run into financial troubles. The increasing level of unfilled demand incentives firms to buy new farms, a tendency that together with the increased number of defaulted farms leads to a sharp increase in market concentration, land concentration, and in the skewness of firm size distribution (Figs. 10A

[28] Here we assume that demand for food grows exogenous, independently of the amount of available food. In the real world, a persistent shortage of food would clearly trigger negative feedbacks, with localized famines and adverse fall-outs to productivity. These dynamics can be easily investigated in the model by making the demand for food endogenous.

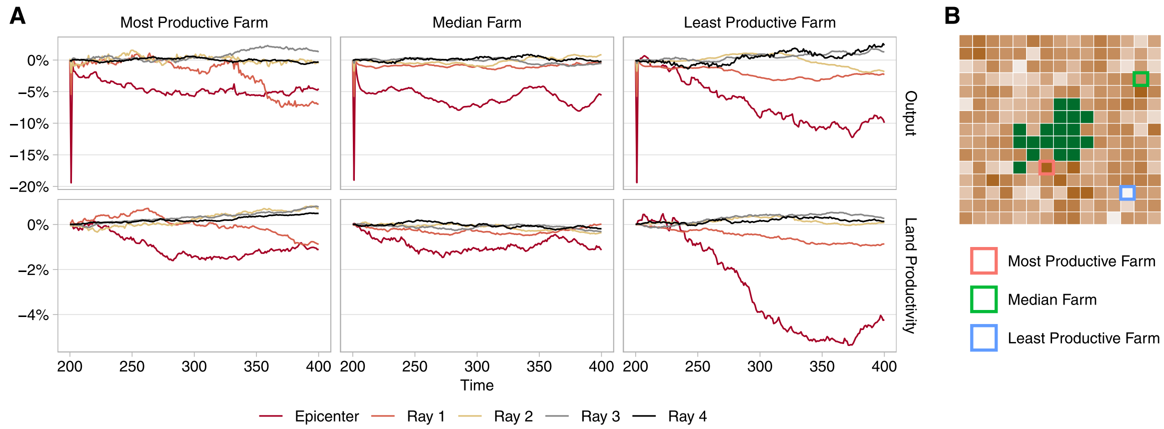

Fig. 11. Climate shocks in the model. Panel A: percentage difference of output and land productivity with respect to the baseline unshocked model, for the three shocked farms. Observations are averaged across Monte Carlo replications and across distances with respect to the epicenter. 50 Monte Carlo replications. Panel B: land productivity and location of the three shocked farms at t_0 — darker cells are more productive. See Table C.8 for further details and significance tests.

and 10D). Land concentration is further exacerbated by the accrued recourse to deforestation, causing a marked diminution in the share of remaining forests (Fig. 10B).

4.3.3. Climate shocks

Extreme weather events are crucial to agriculture (Rosenzweig et al., 2001; Lobell et al., 2011; Claessens et al., 2012; Amadou et al., 2018), and AgriLOVE represents a useful laboratory to study the evolution of food production under several climate scenarios. Here, we begin with a single climate shock, as explained in Section 3.6.3, but we plan to expand the model to accommodate a variegate set of shocks. We draw the shock λ_{it} from a truncated normal distribution $N(\bar{\lambda}, \sigma_{\lambda})$, with $\bar{\lambda} = 0.18$, in line with the figures reported in FAO (2017a). In separate experiments, the shock hits either the most productive farm, the median (in terms of productivity) one, or the least productive one at $t_0 = 200$, allowing the propagation of the climate shock to the neighboring farms according to Eq. (26).[29] The experiment is carried out including deforestation and land abandonment (cf. Section 4.3.1). Fig. 11A shows the effects of climatic shocks both in terms of output and farm productivity for all the three farms considered, expressed as percentage differences with respect to the unshocked baseline.

When the most productive farm is hit, production declines and the difference with the baseline scenario stabilizes around −5% after more than 50 periods. Qualitatively, such findings are consistent with the empirical evidence of permanent damages (e.g. Barrios et al., 2008). The climate shock, which destroys a fraction of output, has a two-fold effect: on the one hand, the inability to satisfy the demand causes an immediate drop in the competitiveness of the farm (Eq. (12)); on the other hand, the shock lowers profits, as a lower level of production is obtained for the same amount of inputs. Both effects have, *ceteris paribus*, the potential to generate a negative path dependence, via lower market shares and lower resources for learning and innovation. Consequently, in the long run we observe a drop in farm productivity. Interestingly, the deterioration of productivity appears to have long-run consequences also on immediately surrounding farms, via less effective imitation, indicating both hysteresis and non-trivial spatial propagation effects. This is chiefly the case in remote developing areas. Indeed, where local imitating mechanisms are particularly strong, a shock hindering the productivity of the most performing farm is likely to generate negative and persistent cascade effects on neighboring farms (Bhatta and Aggarwal, 2016; Morton, 2007). No significant effect is detected for farms with distance from the epicenter larger than one.

These propagation effects appear not to be significant when climate shocks hit the median farm. The average productivity of the median farm discourage the imitation of neighboring farms, which are thus not affected by the initial impact. The drop in the output produced in the epicenter appears instead to be slightly larger than that experienced by the most productive farm. Less productive farms are in fact less capable of counteracting the negative effects of a climate shock due to their initial worse competitive position and lower structural revenues.

Finally, when shocking the least productive farm, short-run losses appear to be typically lower than in other scenarios, while they tend to be markedly higher in the long run, both in terms of output (reaching −10%) and land productivity (more than −4%). Given the low relative productivity of the farm, the effects on the competitive position of the proprietary firm are obviously contained, resulting in mild short-run consequences. However, the scarce resources available in an already weak farm are totally insufficient to counteract long-run consequences; moreover, at the firm level production is shifted towards more productive farms, resulting in a very poor long term performance of the epicenter. Table C.8 reports the cumulative effects on both output and land productivity, with respect to the baseline. Results are in line with those shown in Fig. 11A. Statistical significance tends to obviously decrease both with increasing distance with respect to the epicenter of the shock, and with respect to the time horizon.

5. Conclusions

The present paper introduces AgriLOVE, a evolutionary agent-based model of the agricultural sector. The model focuses on the interactions between technological change, land-use and food production, in an economy exposed to environmental boundaries. Building on the theoretical literature on evolutionary processes of firms' production and interaction (Nelson and Winter, 1982; Dosi et al., 1988, 2010) the paper offers a flexible tool to examine how innovation diffusion, patterns of imitation, behavioral factors and the spatial distribution of productivity and land types might increase or reduce the agricultural sector's ability to cope with an increasing (exogenous) demand for food.

The paper aims at offering a robust assessment of endogenously emerging production regimes in a smallholder farming agricultural sector. Accordingly, the model is parameterized to reproduce realistic behaviors of few key variables (e.g., linear growth in total output, productivity and yields, decreasing food price, productivity-driven decline in employment, increasing market and land concentration, endogenous

[29] As a simulation strategy, we fix the "story" of the model (i.e. the seed for random number generation) until t_0. This ensures that when shock hits, the system is always in the same exact conditions. Fig. 11B shows the state of the grid in terms of land productivity at t_0 and the locations of the three shocked farms. After the random shock is drawn, each run proceeds with a different seed.

heterogeneity and bimodalities in farm productivity). Secondly, we extensively explore the dynamics generated by the model across several scenarios featuring different institutional and behavioral settings. Our results show the crucial role of learning, in the forms of between-firm imitation and within-firm transfer of knowledge. The former is particularly effective at boosting overall productivity, while the latter successfully reduce farm productivity dispersion (although at the expenses of a higher market and land concentration). We also show how higher market selection can increase market and land concentration, leading to bi-modalities in farm productivity distributions. Finally, we show how bi-modalities can emerge from spatial segregation of the least productive farms. Overall, our results suggest that agricultural policies aimed at sustaining yields growth should seriously consider how knowledge is generated and transmitted across heterogeneous farms, as these processes are responsible for market and land-ownership concentration.

By introducing a dynamic discrete choice model between two agricultural regimes, we also demonstrate that food security is adversely affected by unanticipated human-induced soil degradation dynamics. Finally, our results highlight both hysteresis and non-trivial spatial propagation effects in response to localized climate shocks, which can adversely affect system-wide productivity and crop production in the long-run, depending on geography and productivity dispersion across space.

The AgriLOVE model comes with some limitations, which we plan to address in our future research. *First*, the model can be calibrated to specific regions or countries in order to provide more precise quantitative results. *Second*, the model can be extended to account for the use of capital in farms' production and — hence — to include mechanization dynamics that may contribute to structural change and inequality. Capturing capital accumulation dynamics would be especially relevant if one wishes to investigate areas of the world characterized by monocropping at a very large scale, where the role of mechanization is highly relevant (e.g. Brazil and Argentina). This will require a detailed modeling of network relationships between capital good consumers and final purchasers, as well as adoption routines. These modifications should be accompanied by a revised modeled production process, in order to account for the productivity impact of new machinery. *Third*, we currently consider a unique homogeneous crop, which prevents studying specialization patterns as well as adaptation via crop selection and the consequences of different dietary regimes. AgriLOVE can easily be extended to accommodate multi-crop production: discrete choice models akin to that employed here to describe agent choice between agricultural regimes (conventional *vs* sustainable, see Section 3.6.2) are routinely used to represent production choices among alternative crops (see e.g. Moniruzzaman 2015 in Bangladesh, Wang et al. 2010 in China, Seo and Mendelsohn 2008 in South America, and Carpentier and Letort 2014). Such extension could be modeled together with endogenously evolving demand patterns and preferences. Finally, the model does not explicitly account for intermediate inputs (e.g. fertilizers and water) and social network effects across firms (as opposed to within-firm learning). A more complex characterization of information flows between and within firms would further enrich the description of imitation linkages, and could be achieved by super-imposing a network structure over the property and spatial relationships already captured by the model, as in Latynskiy and Berger (2012).

Indeed, our work can be extended in several directions. For instance, the analysis of climate shocks, which constitute one of the major sources of output fluctuations in agriculture, can be further expanded (e.g. impacts to land availability vs. impacts to soil productivity). Finally, the AgriLOVE model can be coupled with macroeconomic agent-based integrated assessment models (as the one developed in Lamperti et al. 2018) to investigate how spatially heterogeneous climate impacts on agriculture affect economy-wide dynamics out of a general-equilibrium setting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data were used. Code is publicly available.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2023.107756.

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