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# LEM

# WORKING PAPER SERIES

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

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

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**Abstract**

This paper presents a novel agent-based model of land use and technological change in the agricultural sector under environmental boundaries, finite available resources and changing land productivity. In particular, we model a spatially explicit economy populated by boundedly-rational farmers 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, farmers 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 on land 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 showcase the properties of model in different applications considering deforestation and land abandonment; soil degradation; and climate impacts.

**Keywords:** Agriculture, Land use; Agent-based model; Technological change; Environmental boundaries; Sustainability.

**JEL codes:** C63, Q15, Q16, Q50, Q55

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# 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 farmers competing to satisfy a growing demand while coping with finite resources and different land productivity, land-management practices and climate-related shocks. The model can be employed to perform scenario analyses featuring different climate, institutional and policy settings (as in e.g. Bert et al., 2011; Berger and Troost, 2014), as well as calibrated to particular areas to perform fine-grained impact assessment analysis (e.g. Troost and Berger, 2015). This paper is devoted to a detailed presentation of the model, its modular structure, code, main properties and possible applications.[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, fibre, 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, savannahs, natural grasslands and wetlands) and declining biodiversity (IPCC, 2019). 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. ABMs' architecture is thus a natural candidate methodology to explore complex socio-ecological systems (Filatova et al., 2013).

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. The model accommodates several mechanisms of environment-agent interactions as well as farmers' behavioral attitudes, and allows the analysis of various scenarios of land degradation, forest and land management, population growth and climate impacts on farmers' activities. Building on the evolutionary theory of economic change, 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. Farmers 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 recently argued in Moser (2020), research, innovation, and knowledge diffusion are key determinants of the short and long run dynamics of agricultural yields.

The complex interactions occurring among heterogeneous farms generate emergent aggregate patterns, capturing some key stylized facts characterizing the micro and macro dynamics of the agricultural

[1] The code of the model is freely available and can be downloaded from `https://github.com/CoMoS-SA/agriLOVE`.

sector. 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 the structural outcomes of the system, such as the distributions of farm size and land productivity. We further show how the non-trivial spatial structure of the model allows the emergence of bi-modalities in land productivity.

We study different applications of the model. First, we allow for deforestation and land-abandonment showing that the microeconomic profit incentives of firms can lead to increasing rates of pristine soil exploitation which ultimately reduce the total crop production. We then study the effects of 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 and discusses future developments.

## 2 Related literature and our contribution

Agent-based models (ABMs) have been fruitfully employed for the analysis of several complex economic phenomena, due to their ability to couple heterogeneity and non-trivial interactions among multiple decision-makers (see for an extensive review Tesfatsion, 2006). Fields of applications of ABMs includes, among others, innovation and technological change (see the review in Zhang and Vorobeychik, 2019; Dawid, 2006), financial and macroeconomic dynamics (see, among others, Fagiolo and Roventini, 2017; Haldane and Turrell, 2018; Dosi and Roventini, 2019; Dawid and Gatti, 2018), labour markets dynamics (e.g. Dosi et al., 2017a) and models of post-disaster recovery (e.g. Henriet et al., 2012). Recently, scholars have also called for an increasing adoption of ABMs to study climate risks across multiple sectors and scales, including applications to the agricultural sector (Mercure et al., 2016; Balint et al., 2017a).

The agricultural sector is increasingly recognized as a complex system, characterized by interdependences across time and space, the presence of disequilibrium dynamics, feed-back loops and tipping points (Van Mil et al., 2014). The ABM literature on agriculture and land-use is vast and has been blossoming in the last decade 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). Similarly, progresses and challenges of the agent-based methodology in modeling coupled socio-ecological systems have been vastly investigated (see, among others Luus et al., 2013; Filatova et al., 2013).

The agriLOVE model contributes to the family of land-use ABMs by offering a novel spatial simulation laboratory to explore how boundedly-rational behaviours, institutional settings and policy interventions influence social and environmental interactions to determine the emergence of regularities in the dynamics of food production, food prices, land productivity and land-use changes. As an innovative feature, agriLOVE focuses on the processes of technological change, knowledge accumulation and diffusion as drivers of productivity growth and market outcomes, which ultimately shape production and prices. More precisely, we build on evolutionary theories of technical change (Nelson and Winter, 1982; Dosi et al., 1988) and industrial dynamics (Dosi, 1984; Dosi et al., 1995; Dosi and Nelson, 2010). In that, our model partially stems from the literature on agent-based modelling of industrial development and long-run growth (Silverberg et al., 1988; Fagiolo and Dosi, 2003; Dosi et al., 2017b), by incorporating standard mechanisms of firm competition, knowledge accumulation and learning into a spatial environment (Dosi et al., 2019, 2020).

Following Le Page et al. (2017)'s classification of modelling abstraction, agriLOVE fits in the intermediate-scale category, where representations typically reproduce patterns in spatial configurations through re-scaling and proportion-matching of real-world settings (see e.g. the FEARLUS model in Polhill et al., 2001). The spatial dimension is explicitly considered through the location of heterogeneously productive lands and forestries on a discrete grid. The model can thus be employed both for theoretical scenario-exploration analyses, and appropriately down-scaled for studies of agricultural sectors calibrated to specific regions, in line with numerous land-use ABMs (see Niamir et al. 2019, Becu et al. 2003 and Groeneveld et al. 2017 for a detailed literature review).

In prioritizing local social interactions (as defined in Le Page et al., 2017), which arise endogenously in the model as agents incessantly adapt their decisions to their flow of limited information regarding an evolving environment, agriLOVE relates to land-use models focused on agents' dynamics dictated by both spatial proximity (as in Thebaud et al., 2001) and social proximity (as in Janssen, 2007; Courdier et al., 2002).

By integrating climate-economy dynamics, our model can be further employed investigate the relationship between climate change and agricultural systems (for a review, see Matthews et al., 2007; An, 2012; Groeneveld et al., 2017; Müller et al., 2020). [2] Similarly, 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). Our model can be employed to address similar issues, while departing from different theoretical premises. Indeed, ABMs are of particular appeal as they allow to relax some (often unrealistic) assumptions on agents' behaviours and their interactions.[3] Finally, our model of agricultural sector may be coupled with the recently developed agent-based integrated assessment models (Balint et al., 2017b; Lamperti et al., 2018, 2019b, 2021), which currently lack representation of land use and cover change dynamics and related emissions.

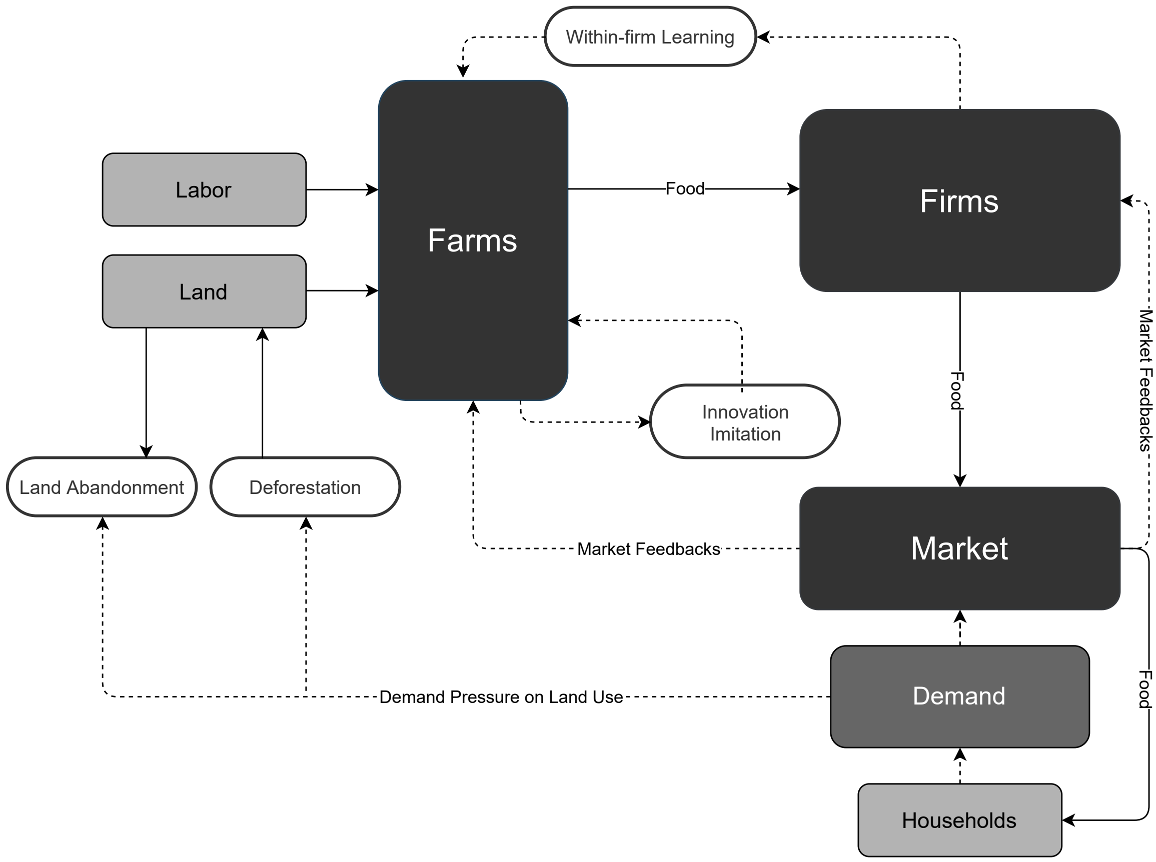


Figure 1: Workflow of the model.

## 3 The agriLOVE model

The structure of the economy portrayed by the model is described in Figure 1. The model is populated by an ecology of $N_t$ agricultural firms, which can own a variable number of farms, thus possibly cultivating multiple plots of land. 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 (kilocalories/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.[4] Additionally, cultivating and harvesting cereals-alike crops do retain around 50% of total carbon

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

[3]Some agricultural ABMs, despite the sequential nature of the operations performed by the agents, still assume fully rational decision makers (see e.g. Monticino et al. 2007), where they are endowed with perfect knowledge about the equations governing the model and the state of each variable.

[4]Focusing on cereals also allows us to avoid peculiar distortions present in the production of e.g. vegetables, wine,

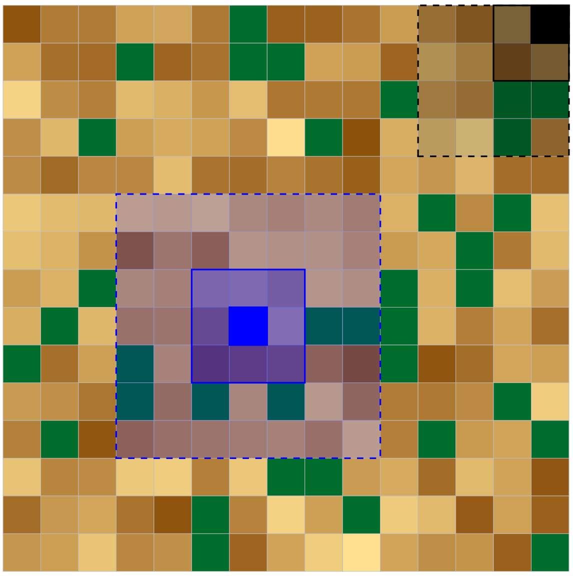

Figure 2: Different observational horizons ($d = 1$ and $d = 3$) from distinct locations on the lattice. Darker cells have higher soil productivities, green cells are forests.

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 Figure 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.[5] 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.

### 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 most 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 accordingly updated (Section 3.4);
4. Profits are computed (Section 3.5). Firms with negative liquid assets go bankrupt, and their land is possibly allocated to surviving firms via auctions or it is abandoned;

biofuels and livestock agricultural markets.

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

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 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 land productivity dynamics

Firms own plots of land characterized by an initial soil productivity $\theta_{i0}$ stemming from predetermined pedo-climatic characteristics (Fatichi et al., 2020), heterogeneously distributed across the grid (Figure 2). In order to increase their profits, farmers strive to improve productivity by innovating, imitating neighbouring farms, and learning the best agricultural practices and techniques of the firms to which they belong (e.g. Conforti, 2017).

*Innovation* activities in the model encompass all those practices and procedures prone to improve seed, land management, resource and soil quality (Fischer et al., 2012). In industrial farming systems, such processes usually boil down to an increased quality of inputs (e.g. blended fertilizers), while in low-input farming systems technological advances more often take the form of improved crop cultivars and alternative irrigation practices. We model innovation as a technology-based process (Coomes et al., 2019), through a two-step process akin to Dosi et al. (2010). First, farms devote a fraction $r^{IN}$ of their previous period's revenues to innovation activities:

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

where $S_{it-1}$ represents sales (in terms of bundles of food) and $p_{t-1}^{food}$ is food price. A higher innovation expenditure $\mathrm{EXP}_{it}^{IN}$ increases the chance of successfully innovating. Whether a farm successfully innovate, is determined through a Bernoulli trial, with probability

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

where the parameter $\iota$ captures the effectiveness of innovation expenditures.[6] In case of successful innovation, the productivity improvement entailed by the new practice $\mathrm{IN}_{it}$ 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.[7]

*Imitation* is an extremely common practice in agriculture: 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 in both developed and developing rural contexts. Alike innovation, imitation is modeled as a two-steps process, and is assumed to be a costly process, reflecting set-up costs for introduction of new techniques (MacLeod et al., 2005), barriers (e.g. educational and institutional) to imitation (Brenner, 2006) as well as formal R&D investment. In short, both inno-

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

[7]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 both in developed and developing countries 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).

vation and imitation require acquiring and mastering new knowledge, and both these processes are costly. Farms allocate part of their revenues $r^{IM}$ to imitation:

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

Naturally, $r^{IN} + r^{IM} \leq 1$. The probability of successfully imitating is regulated again by a Bernoulli trial, with probability[8]

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

Given the relevance of geographical proximity (Moss et al., 2000), imitation happens between spatially close cells (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 $N_{it}^{IM}$ within a given ray $d^i$ (cf. Figure 2), and it selects the most productive farm in $N_{it}^{IM}$:

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

The imitating farm is then allowed to get closer to the imitated farm in the technological space (see Equation 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 frequently registered in case of multinational acquisitions (Swinnen, 2007), as well as in family farming systems, where plots of a single producer are rented out to numerous families (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 same organization.

Overall, the dynamics of soil productivity ($\theta_{it}$) is affected by innovation, imitation and within-firm learning. We assume that the knowledge acquired across these three processes allows farms to improve their soil 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 $\theta_{it}^{IM}$. An analogous mechanism governs the influence of the most productive farm within each firm ($\theta_{it}^{W}$). Second, innovation is assumed to boost productivity independently from the outcome of the imitative process. Hence, productivity dynamics reads

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

where the parameter $\mu_I$ 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, [9] and allows us to jointly explore the contribution of both imitative processes to the model dynamics (see Section 4.2.1 and Appendix

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

[9]For example, there is evidence that farmers in the US corn belt region as well as in sub-Saharan Africa explore new technological options displaying intrinsic synergies (Sunding and Zilberman, 2001; Chavas and Nauges, 2020).

D and E). Of course, a variety of alternative laws of motion for productivity are possible, depending on whether innovative efforts, imitation and learning are treated as complements or substitutes. [10]

### 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:

$$Y_{it} = \theta_{it} L_{it}^{\alpha} S_{it}^{1-\alpha}, \tag{7}$$

with $0 < \alpha < 1$, which ensures constant return to scale (typical of ceral production, as in Bardhan (1973); Kislev and Peterson (1996)) and diminishing returns from labor, which constitute standard assumptions when modeling agricultural sectors. As the number of plots of lands are predetermined, wihtout 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 cells owned by firm $z$.

Firms adjust their employment according to the evolution of their demand. In industrial settings, this operates through firing or hiring of workers, while in family farming contexts, the adjustment mechanism is frequently accompanied by a migration of the excessive supply of labour from rural to urban jobs. First, firms compute their unfilled demand ($UD_{zt}$):

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

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 $\epsilon_L$ 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 $\theta_{zt}$ is the average productivity of farms owned by firm $z$. Each cell has a limit $L^{max}$ to the amount of workers which can operate on it, reflecting again decreasing marginal returns from labor.[11] 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

[10] 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: $\theta_{it}^{I} = \max\{\theta_{it}^{IM}, \theta_{it}^{W}\}$. The resulting equation for the evolution of farm productivity would then become $\theta_{it} = (1 - \mu_I)\theta_{it-1} + \mu_I \theta_{it}^{I} + \mathrm{IN}_{it}$.

[11] If the resulting labor force in cell $i$ is greater than $L^{max}$, then the difference is reallocated iteratively among the remaining cells, 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.

wage bill is higher than a fixed share $\zeta$ 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 both industrial agricultural markets, as well as 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 $\mathrm{ED}_t = \frac{D_t - Y_t}{Y_t}$:[12]

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

where $\epsilon_p$ 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, see e.g. Dosi et al. 2010; Chiaromonte and Dosi 1993):

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

with $\epsilon_{MS} > 0$. The fitness or competitiveness $F_{zt}$ is given by the inverse of a linear combination of unfilled demand $UD_{zt}$ and firm (inverse) efficiency $\Upsilon_{zt}$, whose relative weights are governed by the parameters $\omega_1$ and $\omega_2$:

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

Positive values of unfilled demand decrease firms' fitness, reflecting inability at satisfying the demand they face. Unfilled demand ($UD_{zt}$, cf. Equation 8) allows to capture the effects of frictions associated with production asymmetries - e.g. asymmetric access to markets, transportation costs.[13]. The other fundamental factor affecting the evolution of firms' market shares is land productivity. 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 land productivity.[14] The

[12] For the sake of simplicity, no technological agricultural treadmill hypothesis (Ward, 1993) is considered.

[13] Frictions can be substantial in marginal rural markets of both developed and 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 and Bacior and Prus 2018)

[14] In order to keep the disturbance relevant as the economy grows, we assume $\mu_t^{\Upsilon}$ to increase at the average rate of growth of soil productivity $\Delta_t^{\theta}$. Thus $\mu_t^{\Upsilon} = \mu_{t-1}^{\Upsilon}(1 + \Delta_t^{\theta})$.

firm-level indicator of efficiency $\Upsilon_{zt}$ is simply the weighted average of the indicators of each owned farm, with weights given by the output produced by each farm. As $\Upsilon_{zt}$ enters the fitness at the denominator, higher values of $\theta_{it}$ (the main determinant, besides labour, of the volume of output produced by each farm) are associated, ceteris paribus, with larger market shares. Especially in cereal-based developed markets, large processing food companies tend to favour more productive farms, which can guarantee higher quantities of products. For instance, this grants the processing company a more homogeneous final output, derived by few highly-productive suppliers (Sivramkrishna and Jyotishi, 2008). Large buyers of agricultural products have thus incentives to deal with firms entailing relatively more productive farms, which can reliably supply high quantities of food (MacDonald et al., 2018).

Thus, by ameliorating the productivity of their soils, firms 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. As we shall see, the coupled dynamics of labor demand 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.[15]

### 3.5 Profits and land re-allocation

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

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

This modeling decision fairly approximates the complex determinants behind land price establishment (Hallam et al., 1992). 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 cell to be sold with respect to those owned by the bidder; ii) the demand pressure

[15]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. $\min\{D_t, Y_t\}$.

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 $\epsilon^A$ is a parameter and $d_{ij}$ is the distance between the cell on sale $i$ and the closest cell among those owned by bidder $z$, cell $j$. 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 cell $j$, paying a price equal to $B^2$.

After the auctions, some plots of land can be unsold. We consider two scenarios. In the first one, we assume that cells 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 cells are abandoned, and 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 both in developed countries (especially in Europe, Mather, 2004) and developing ones (Mather, 2007).

## 3.6 Prospective applications: 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 abandoment (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

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

where $\epsilon_f$ 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 productivity of new arable land is equal to that of the conventional farm which undertook the deforestation action, plus a fixed proportion $\Delta^f$ 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 will be 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). In fact, 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 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 Figure B.1), but they lead to long-run soil depletion. On the contrary, sustainable farms preserve the soil nutrients, but their productivity is lower. Analytical details are provided in Appendix B. Soil degradation impacts negatively on soil productivity trough the term $\mathrm{SD}_{it}$. Therefore, Equation 6 now becomes:

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

where $\mu_{IM}$ and $\mu_W$ are analogous parameter to $\mu_I$ in Equation 6. We assume that $\mathrm{SD}_{it}$ depends on the number of time periods $T^c_{it}$ in which the cell $i$ has been producing in a conventional regime, and evolves according to a logistic function (see Equation B.1 and Figure B.1). 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.

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). The firm attempt to switch whenever the amount produced by the set of farms employing a different technique is higher than that produced by the set of farms employing the same technique as the firm in question. Analytical details are given in Appendix B. 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 cell $i$ at time $t$, destroying a fraction $\lambda_{it}$ 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 the impact is:

$$Y_{it} = \lambda_{it} Y^*_{it}, \tag{22}$$

where the shock $\lambda_{it}$ 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 cells $j$, and the effects decays with the distance $d_{ij}$ between the origin of the event $i$ and the neighbouring cell $j$, according to:

$$\lambda_{jt} = exp(-\epsilon_{\lambda} d_{ij}) \lambda_{it}, \tag{23}$$

where $\epsilon_{\lambda}$ is a parameter tuning the spatial rate of decaying of extreme events intensity.

## 3.7 Model setup and simulation strategy

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 error),[16] although representative single runs are sometime shown to illustrate a prototypical behaviour.

The model is initialized and parameterized to capture global level proportions and reasonably resemble realistic dynamics. A typical run consists of 400 periods, after a "warm-up" phase of 100 periods required to remove transient dynamics.

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 (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

[16] 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., 2020).

on the diffusion of organic agriculture.[17] 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 thereby explore the parameter space and validate the model in order to reproduce a set of real-world 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). The list of baseline parameter values is reported in Table C.1, while the details of the baseline model initialization are given in Table C.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 encompass any soil depletion phenomena, 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), soil degradation and sustainable farming (Section 4.3.2), and climate shocks (Section 4.3.3).

## 4.1 Validating the *Plain Vanilla* model

The model replicates a pool of micro and macro stylized facts of the agricultural sector. The baseline scenario (not encompassing any type of environmental boundary) depicts in fact a healthy economy, as summarized in Figure 3 and Table 1. The model generates a linear growth in total output (Figure 3A), as observed in global data on cereal production (Figure 3J). Such increase has been in turn driven by an analogous growth in yields (Figure 3K). Indeed, soil productivity in the model (shown in Figure 3K at the micro/cell level) evolves, on average, in a linear way. Food price slightly decreases over time (Figure 3C), as confirmed by empirical evidences, especially in developed economies (Christian and Rashad, 2009). The growth in output is coupled with a secular decrease of employment in the agricultural sector (Figure 3C). This result matches a long-lasting trend observed in the real world (Mueller and Chan, 2015), as labour force have progressively left - with different magnitudes across the globe - the primary sector (Figure 3C). This aggregated trend hides nonetheless a remarkable heterogeneity at the farm level (Figure 3G), with single farms experiencing periods of rising employment, in the attempt

[17]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.

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).

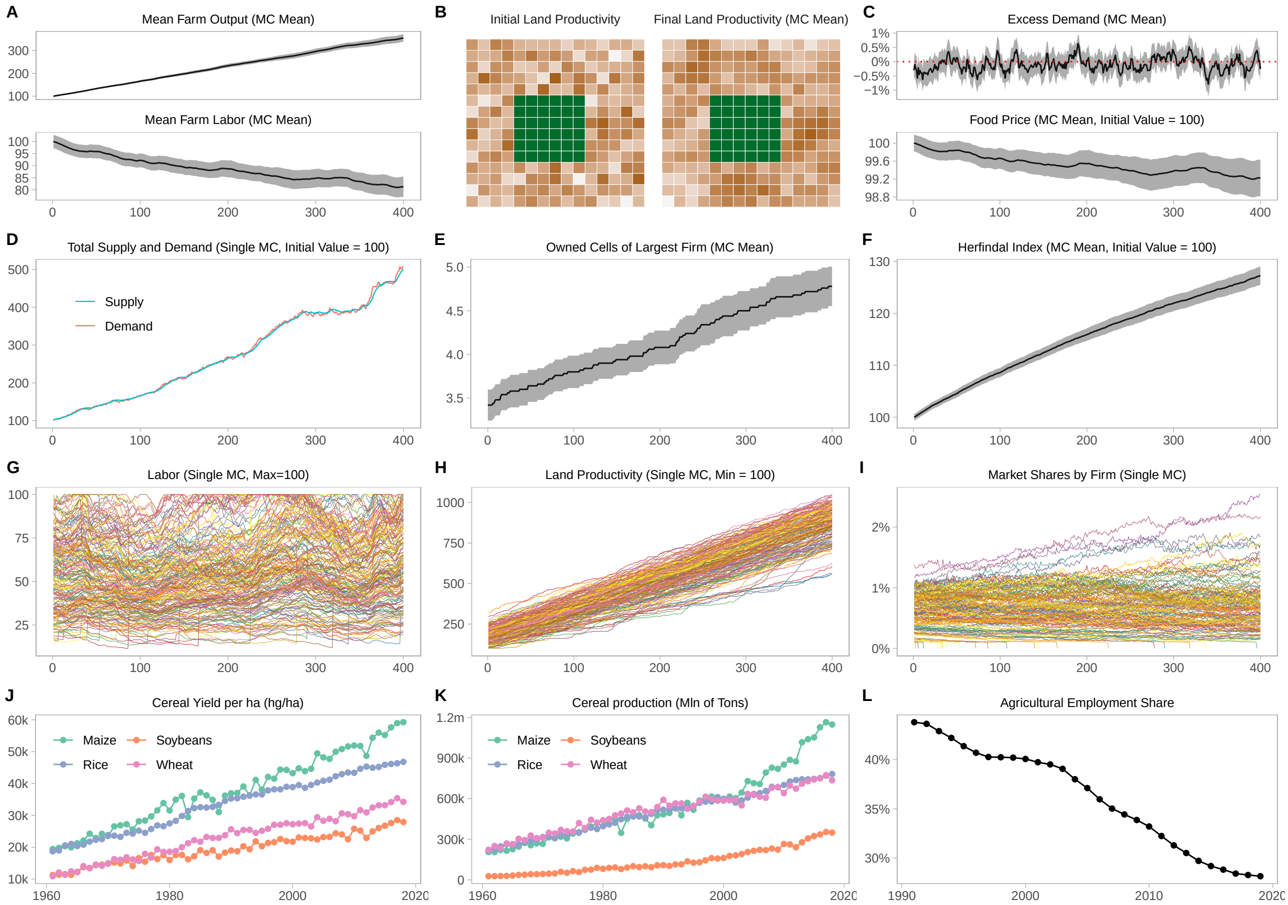


Figure 3: Panel A to I: Baseline model results. Horizontal axis showing time steps. 50 Monte Carlo replications. Shaded areas are 95% confidence bands. Panels J to L: Long-run evolution of agricultural output, yield and employment at global level. Horizontal axis showing years. Agricultural employment expressed as percentage of total employment. Sources: FAOstat and World Bank.

Heterogeneity among farms tends to evolve over time. Initial land productivity, while giving a remarkable competitive advantage (Table 1 documents a correlation of 0.72 between initial and final land productivity), represents no guarantee of success over time. 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 Pardey, 2020). Figure 3B highlights the importance of initial land productivity, while stressing the emergence of locally clustered areas of higher 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 (Figure 3K). Market dynamics are more evident when looking at firm market shares (Figure 3I), 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 (Figure 3H), in line with the empirical evidence (Vickner and Davies, 2000). These dynamics, coupled with positive feedbacks between innovation, land productivity and market shares, gives rise to an increasing Herfindal Index (Figure 3I), testifying a growing market concentration (Howard, 2009). The system is able, on average, to serve the global demand for food, despite short-run fluctuations stemming from micro-level shocks and coordination failures (Figure 3C. The economy produces on average slightly

Table 1: Summary statistics for baseline model. 50 Monte Carlo replications. Monte Carlo standard errors between parenthesis.

| | Excess Demand (%) | Food Price (% Initial-Final Change) | Bankrupts (% of Initial Firms) | Mean Output Growth (%) | Land Productivity (Inital 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)* |

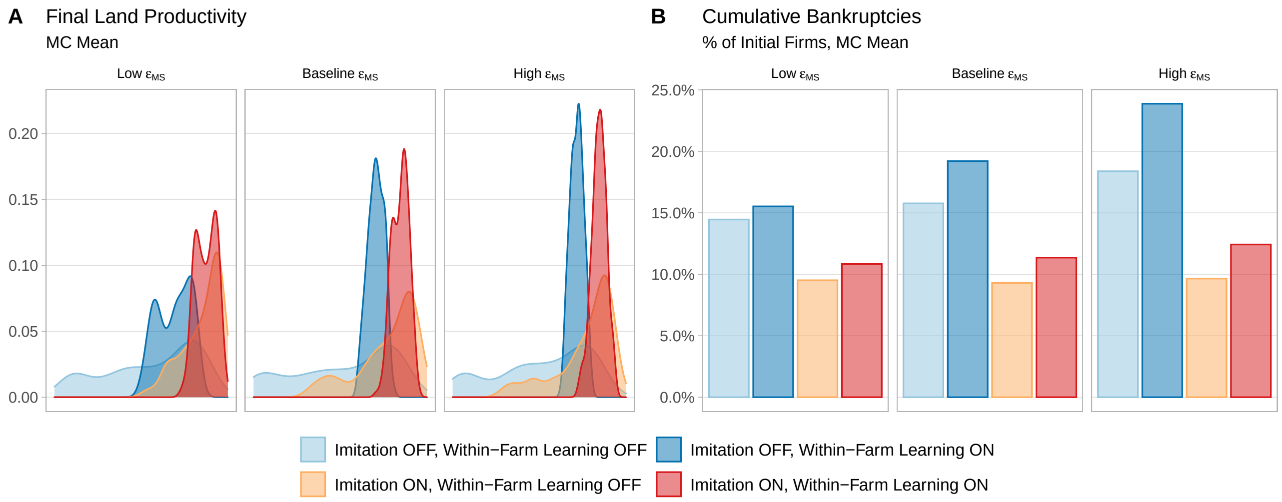


Figure 4: Land productivity and bankruptcies for different levels of imitation, within-firm learning and replicator dynamics intensity ($\epsilon_{MS}$ values: low $\epsilon_{MS} = 0.2$, baseline $\epsilon_{MS} = 0.5$, high $\epsilon_{MS} = 0.8$). 50 Monte Carlo replications. See Table D.4 for further details.

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 D.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 Exploring the model

### 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 cells are more likely to happen among neighboring farms (Equation 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 $\epsilon_{MS}$, which captures different strengths of market selection.

Learning mechanisms appear essential to influence both the mean and the dispersion of land productivity in the model (Figure 4A and Table D.4), although in a different fashion. Imitation reduces land productivity variance, but its primary role is to remarkably rightward shift the productivity distribution by accelerating technological diffusion. This is in accordance with established global dynamics of technological imitations 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 learning on mean land productivity is statistically significant, but milder with respect to imitation (Table D.4). On the other hand, it reduces land productivity

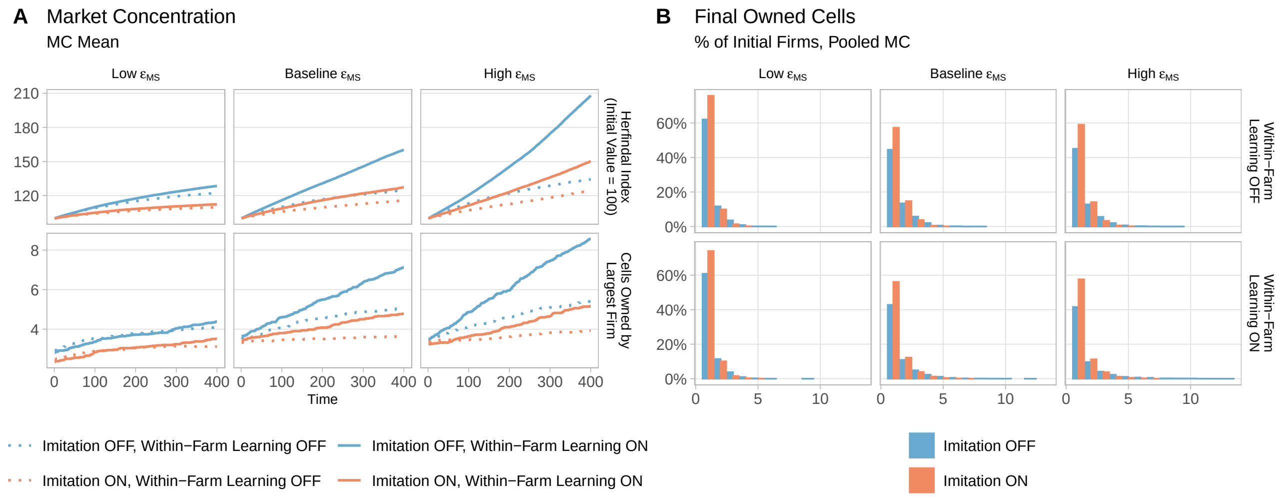


Figure 5: Market and land concentration for different levels of imitation, within-firm learning and replicator dynamics intensity ($\epsilon_{MS}$ values: low $\epsilon_{MS} = 0.2$, baseline $\epsilon_{MS} = 0.5$, high $\epsilon_{MS} = 0.8$). 50 Monte Carlo replications. See Table D.4 for further details.

dispersion more effectively. As a matter of fact, smaller and impoverished lands 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 (Figure 4A), as the number of farms acquisitions increases (Figure 4B). Within-firm learning has thus a twofold nature: on one side, it favours 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 Herfindal index, within-firm learning has the opposite effect (Figure 5). 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 (Figure 5B). 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 evidences on farm size (Wegerif and Guereña, 2020). Such skewness appears to be less pronounced 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 D.4), 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 D and E, we explore the robustness of these findings by varying intensity of both imitation and within-firm learning effects (i.e. $\mu_{IM}$ and $\mu_W$). The results (Figure E.1 and Table D.5) document dynamics which are in line whit those described above.

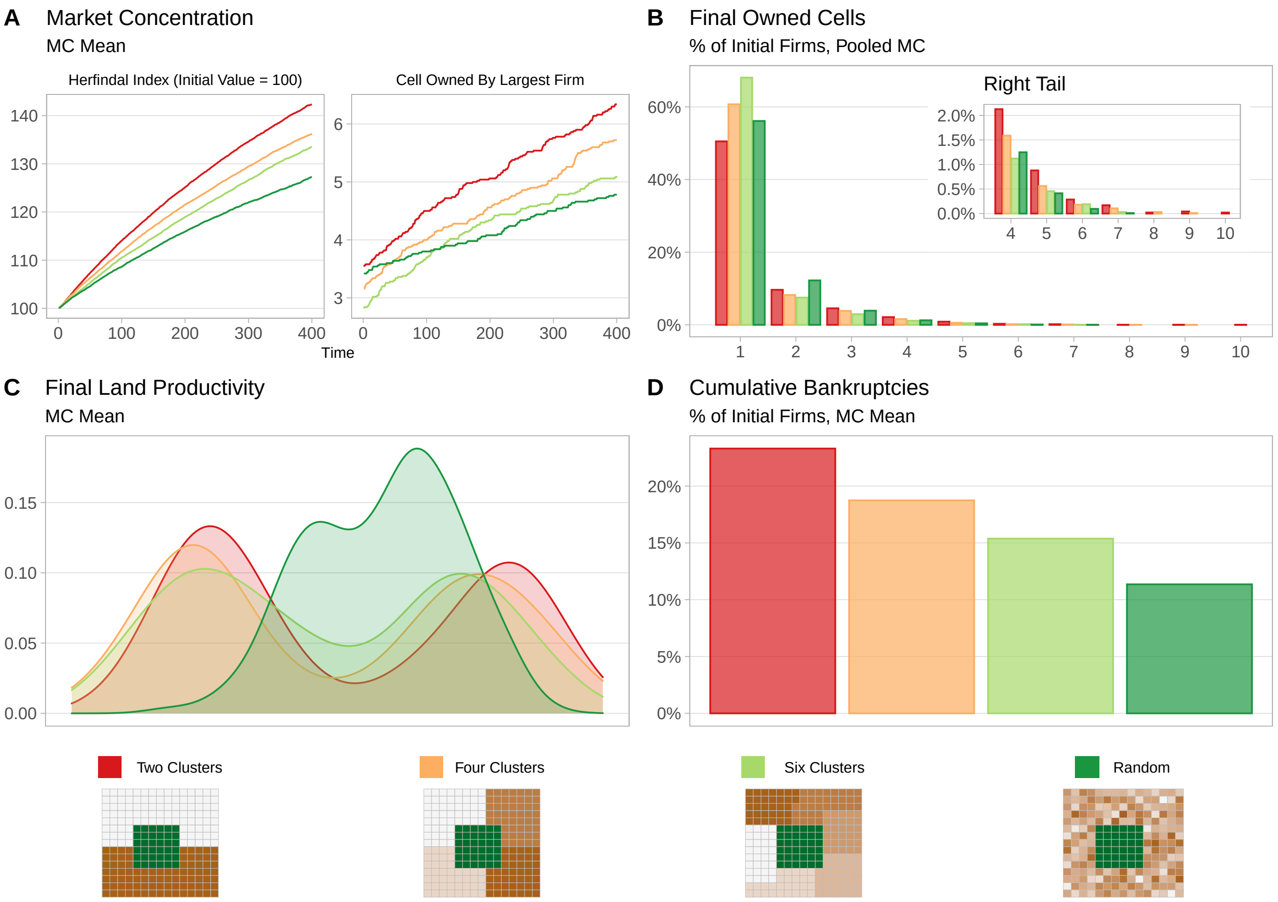


Figure 6: Results for different spatial scenarios of initial land productivity. 50 Monte Carlo replications. See Table D.2 for further details.

### 4.2.2 Spatial distribution and productivity

We here explore how different initial spatial configurations of land productivity affect the dynamics of the model. We consider four spatial scenarios (cf. Figure 6), 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, 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 land concentration (Figure 6A), a more skewed distribution of firm size (Figure 6B) and a higher number of bankruptcies (Figure 6D), without decreasing food price (Table D.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 plots is not entirely counterbalanced by the advantages of clustering together more productive cells: Table D.2 documents significantly lower mean productivity in segregated scenarios, as well as higher variance. The importance of local interactions is well evident in Figure 6C: 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 countries 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 firms, increases land concentration, an effect which in turn causes also an upsurge in market concentration (Figure 7A). This translates in a more skewed distribution of firm sizes (Figure 7D). 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 (Figure 7C). On the other hand, mean productivity is significantly lower (Table D.3). The acquisition of new land allows deforesting firms to successfully expand their production, thereby increasing their market shares. The increased concentration partially crowds-out smaller farms, which are therefore less able to innovate and imitate, lowering in turn the aggregate performance. These dynamics reflect empirical evidences on the vicious effects of deforestation. An example is represented by the acquisition of virgin land in the Amazon, which has increased the competitive power of deforesting firms, while preventing market access to smallholder farmers in the same area, leaving the system with higher market concentration but lower land productivity at the aggregate level (Andersen et al., 2002).

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 (Figure 7B). 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 D.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).

### 4.3.2 Soil degradation

We investigate transition dynamics when allowing for heterogeneous agricultural techniques (conventional vis-á-vis sustainable) and soil depletion (Section 3.6.2). Agents infer the soil productivity and the soil depletion rate implied by their technological choices by observing their output, as well as

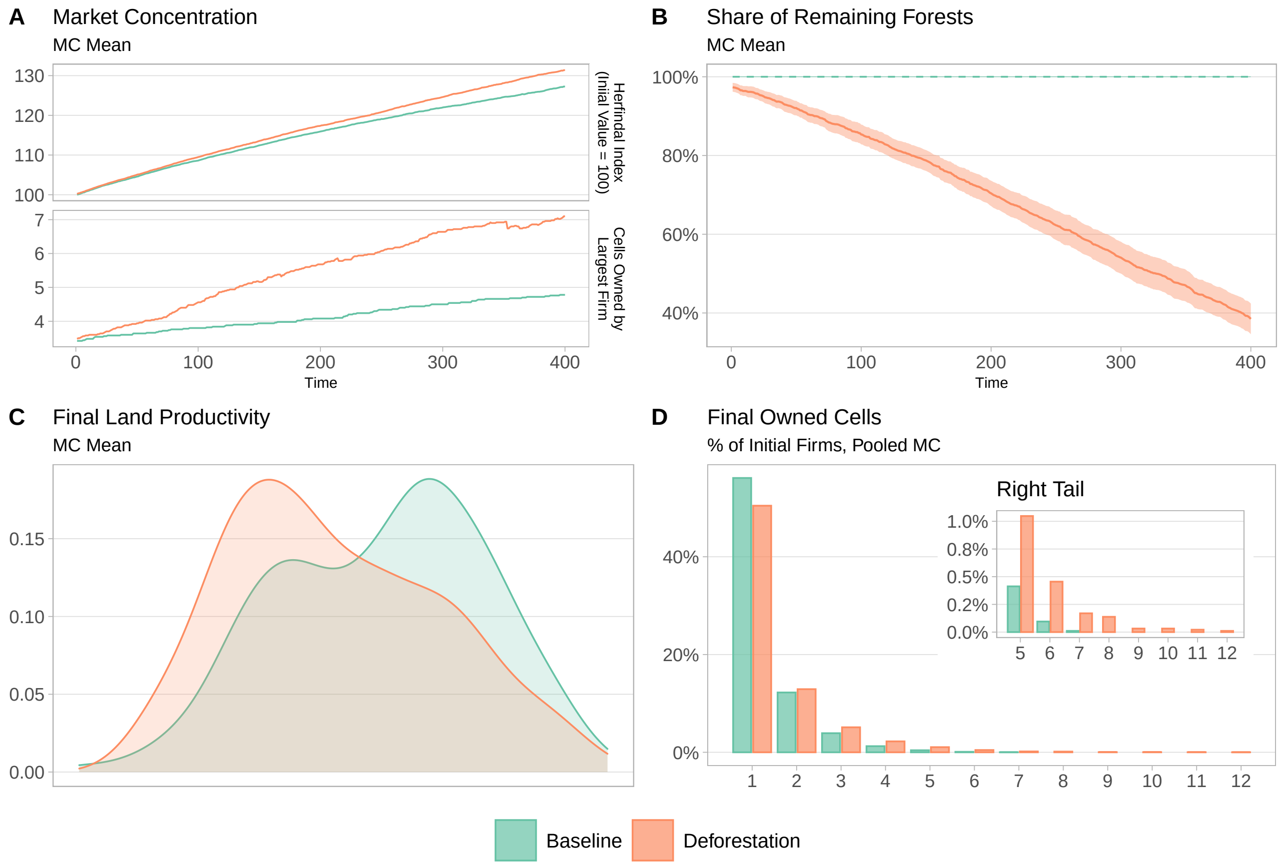


Figure 7: Results with deforestation and land abandonment, and without (baseline). 50 Monte Carlo replications. Shaded areas are 95% confidence bands. See Table D.3 for further details.

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 soil degradation then reduces the productivity of intensive production techniques, possibly triggering the transition towards sustainable farming.

Figure 8 shows two runs exemplifying the limiting cases the model is able to generate. In the first scenario, sustainable farming spread gradually in the lattice as the first signs of 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 Figure 8), 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 soil depletion, resulting in a *lock-in* scenario (right quadrants of Figure 8). Losses from soil degradation accumulate, slowing down soil 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 soil degradation have been abundantly documented for different types of crops (Lal, 2004).

Comparing the dynamics of the model with soil depletion against the baseline scenario provides further insights. In presence of soil depletion, 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

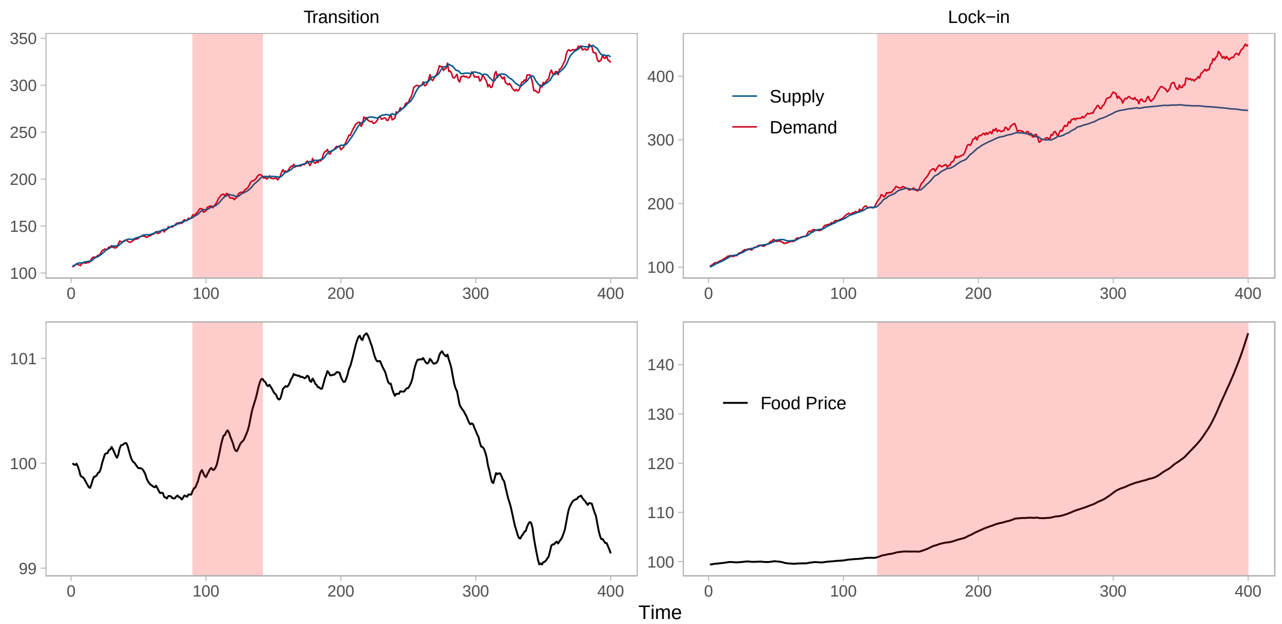


Figure 8: Transition and lock-in scenarios in the model. Two different single runs of the model, exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming and conventional lock-in. For each run, distance between total demand and supply and food price dynamic are shown. Red areas correspond to periods of insufficient food supply.

the baseline scenario with no soil depletion, the system obviously always converge to intensive farming, which is the most productive technique. With soil depletion, 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 (Figure 9C).[18] Due to stagnating (or even descending) levels of land 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 (Figures 9A and 9D). Land concentration is further exacerbated by the accrued recourse to deforestation, causing a marked diminution in the share of remaining forests (Figure 9B).

[18] 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.

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

| | **Transition Dynamics** | | | **Macro Variables** ($t = 400$) | |
|---|---|---|---|---|---|
| | Lockin Probability | Transition Probability | Intermediate Cases | Excess Demand (%) | Remaining Forests (%) |
| Soil Degradation | 78% | 16% | 6% | 11.88% | 12.33% |
| Baseline | 100% | 0% | 0% | 0.11% | 41.11% |

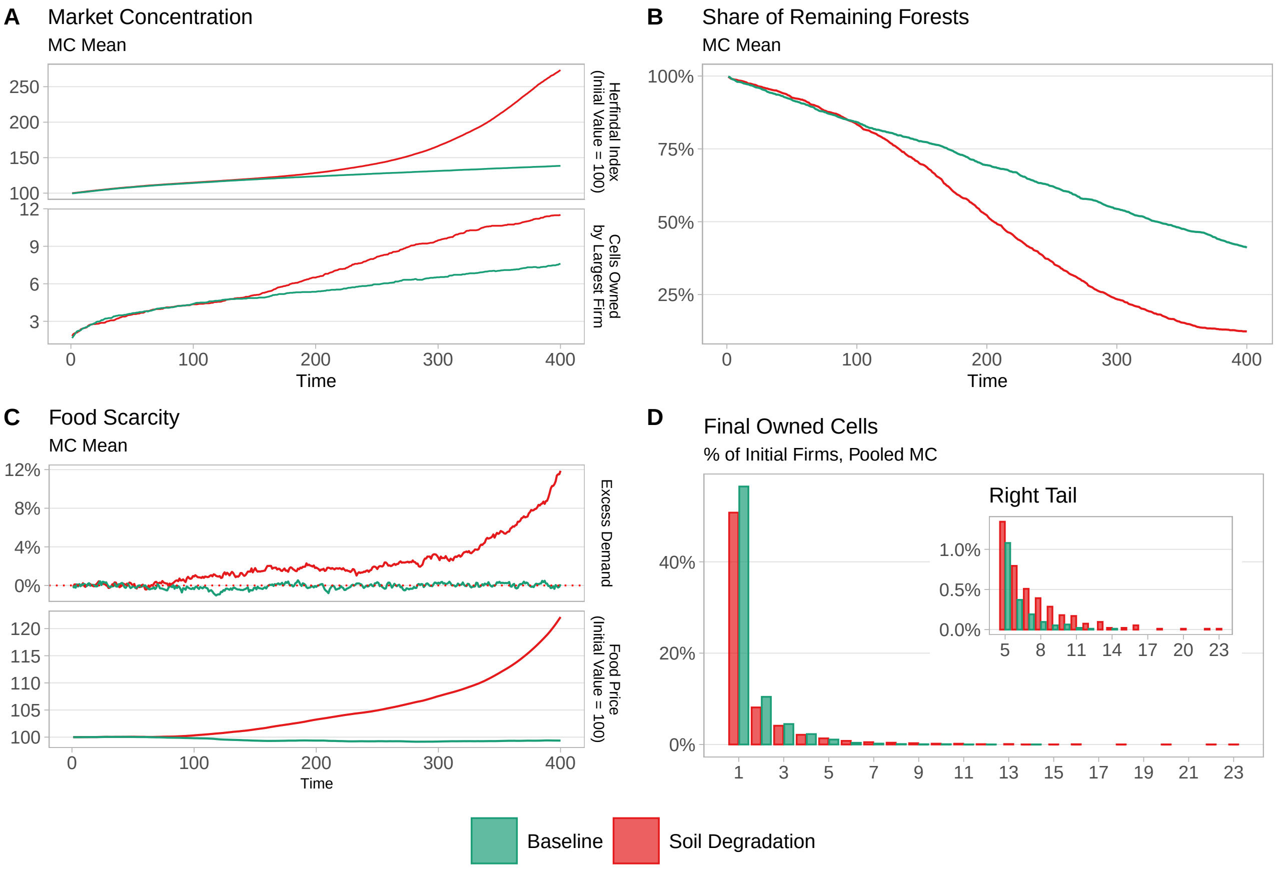


Figure 9: Results with soil degradation and without (baseline). 50 Monte Carlo replications. As soil degradation and regime switching introduce a source of non-ergodicity in the model, in order to keep the location of sustainable/conventional farms constant during the transient, we suspend auctions and 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.

### 4.3.3 Climate shocks

Extreme weather events are crucial to agriculture (Rosenzweig et al., 2001), both in developing (Houghton et al., 2001) and developed countries (Hammer, 1999). 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. More precisely, we draw the shock $\lambda_{it}$ 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 cells according to Equation 23.[19] The experiments is carried out in the model with deforestation and land abandonment (cf. Section 4.3.1). Figure 10A shows the effects of climatic shocks both in terms of output and land 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 decline and the difference with the baseline

[19] 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. Figure 10B 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.

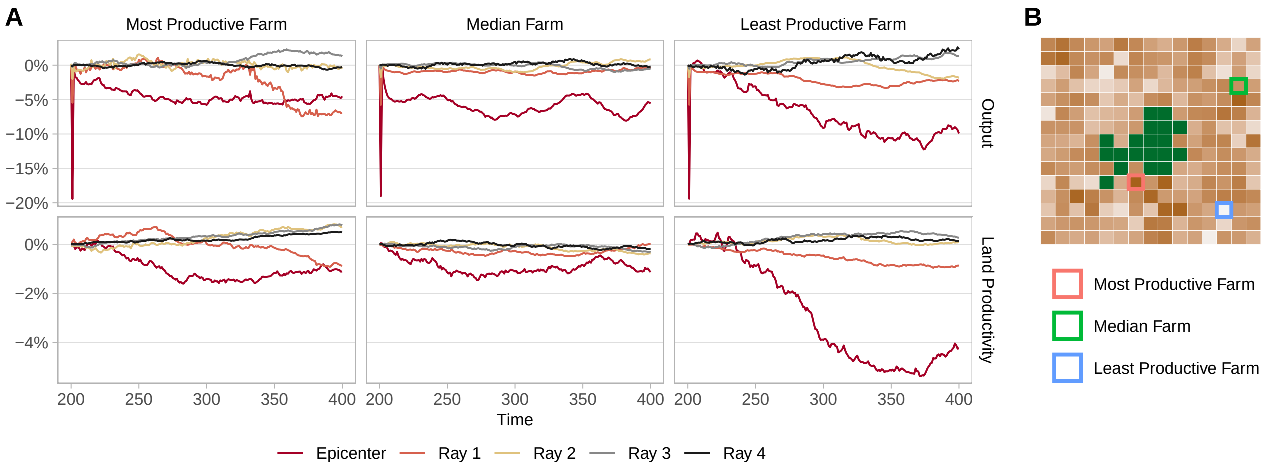


Figure 10: Climate shocks in the model. Panel A: percentage difference of output and land productivity with respect to the baseline unshocked model, for the three shocked cells. Observations are averaged across Monte Carlo replications and across distances with respect to the epicenter. 50 Monte Carlo replications. Panel B: land productivity and location of the three shocked cells at $t_0$ — darker cells are more productive. See Table D.6 for further details.

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 destroy 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 (Equation 12); on the other one, 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 land 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 cells (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 cells, 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 D.6 reports the cumulative effects on both output and land productivity, with respect to the baseline. Results are in line with those shown in Figure 10A. 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.

We firstly replicate key stylized facts of the agricultural sector (e.g., linear growth in total output, productivity and yields, decreasing food price, productivity-driven decline in employment, increasing market and land concentration, endogenous heterogeneity and bimodalities in land productivity). We then 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 land 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 land 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 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.

Our work can be extended in several directions. *First*, the model can be calibrated to specific regions or countries in order to provide more precise quantitative results. *Second*, 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). *Third*, the agriLOVE model might 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.

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# Appendices

## A Code structure

agriLOVE code is written in R and can be freely downloaded from the authors' GitHub repository.[20]. In a nutshell, the file `main.R` contains the main loop structure of the model, and calls to several functions, each implementing a different task along the timeline of the events detailed in 3.1. Code A.1 reports the structure of `main.R`.

The file begins by running four auxiliary files, which contains preliminary operations that need to be performed before the simulation starts. The file `flags.R` contains the various flags which can be manipulated to turn on or off several features of the model (e.g. deforestation, conventional and sustainable farming, soil degradation, various types of initialization). In the file `declarations.R`, all the various arrays are created. For example, the array containing cell productivities is a 4-dimensional array: two dimensions indicating the position of each cell in the grid, one dimension indicating the point in time, one dimension indicating the Monte Carlo replication; the array containing firms wealth will then be, by the same logic, 3-dimensional. The file `parameters.R` contains a comprehensive list of all parameters in the model, where they can be tuned. Finally, the file `initialization.R` fill the various arrays with initial values, i.e. for $t = 1$, along all Monte Carlo replications (initialization is constant across them).

The main structure of the simulation is given by two nested loops: the inner one scrolls the instant of time, the outer one replicates each run of the model with a different seed for pseudo-random number generation, scrolling thus the various Monte Carlo replications. For each step in the time loop, the code replicate the following steps:

1. The function `preliminary_f()` operates preliminary operations on arrays (e.g. update wages, land use arrays).

2. A loop is opened to scroll firms: for each of them, the function `hire_f()` computes the desired labor force at the firm level and how to redistribute them across owned farms (Section 3.3). The loop is closed.

3. Two nested loops are opened, one scrolling the horizontal dimension of land, one the vertical dimension, thus scrolling each cell in the grid. For each cell/farm, the function `rd_f()` determines innovation and imitation outcomes, as well as within-firm learning (Section 3.2). Soil degradation impact is computed if present (Section 3.6.2). Soil productivities are updated, taking into account climate shocks generated in the previous time step, if present. Food production at cell is then level is computed (Section 3.3). Both loops are closed.

4. The function `production_f()` computes food production at the firm level, updates fitnesses and market shares for each firm (Section 3.4).

5. The function `market_f()` replicates the algorithm described in Section 3.4, through which sales are assigned to each firm given the current level of demand and their market shares. Food price is determined.

[20] https://github.com/CoMoS-SA/agriLOVE

Code A.1: Code structure of `main.R`.

```
set.seed(1)                                                   # seed for pseudo-random number
    generation
source("flags.R")                                             # flags module
source("declarations.R")                                      # objects creation module
source("parameters.R")                                        # parameters module
source("initialization.R")                                    # initialization module

#### Simulation ####
for (p in 1:mc) {                                             # scroll Monte Carlo replications
    set.seed(p)                                               # seed for pseudo-random number
        generation
    for(t in 2:time) {                                        # scroll time
        preliminary_f()                                       # preliminary module
        for(z in 1:dim(existing_producers)[1]) {              # scroll firms
            hire_f()                                          # labor module
        }
        for(i in 1:x){                                        # scroll land horizontally
            for(k in 1:y) {                                   # scroll land vertically
                rd_f()                                        # innovation module
            }
        }
        production_f()                                        # producer production module
        market_f()                                            # market module
        for(i in 1:x){                                        # scroll land horizontally
            for(k in 1:y) {                                   # scroll land vertically
                profit_f()                                    # profit module
            }
        }
        p_profit_f()                                          # producer profit module
        for(z in 1:dim(existing_producers)[1]) {              # scroll firms
            switch_f()                                        # switch agriculture module
            entry_f()                                         # entry/auction module
        }
        weather_f()                                           # climate shocks module
        deforestation_f()                                     # deforestation module
    }
}
```

6. Two nested loops scrolls the grid and the function `profit_f()` computes profits and costs (Section 3.5) at the cell level. The loops are closed. Profits and costs are then computed at the firm level through the function `p_profit_f()`.

7. A loop is opened to scroll firms. For each of them, the function `switch_f()` determines whether they change or not their agricultural technique (Section 3.6.2). The function `entry_f()` check whether each firm has negative wealth and, if any, perform auctions on each cell owned by them, reassigning new properties and updating net worths. The loop is closed.

8. The function `weather_f()` computes climate shocks output (Section 3.6.3).

9. The function `deforestation_f()` scroll existing forests and determines whether any of them is turned into arable land or not, updating all arrays relative to the newly established farm (Section 3.6.1). Reforestation happens.

## B Conventional *versus* sustainable agricultural regime: Details

Soil degradation $\mathrm{SD}_{it}$ is given by:

$$\mathrm{D}_{it} = A + \frac{K - A}{1 + e^{-b(T_i^c - M)}} \tag{B.1}$$

where $T$ is the number of period for which the field has been cultivated with conventional techniques, $b$ 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. 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 $\mathrm{SD}_{it}$).

Switching behavior:

$$\gamma_{zt}^S = \frac{exp\left(\tau \cdot \frac{1}{\#(S_{zt})}\frac{1}{m}\sum_{k\in[t-m,t]}^{i\in S_{zt}} \frac{Y_{ik}}{L_{ik}}\right)}{Z_{zt}} \tag{B.2}$$

$$\gamma_{zt}^C = \frac{exp\left(\tau \cdot \frac{1}{\#(C_{zt})}\frac{1}{m}\sum_{k\in[t-m,t]}^{i\in C_{zt}} \frac{Y_{ik}}{L_{ik}}\right)}{Z_{zt}} \tag{B.3}$$

with $Z_{zt}$ being the sum of the two numerators. The quantities between parenthesis are just the average output produced in the last $m$ periods by neighboring sustainable and conventional farms, multiplied by a parameter $\tau$ 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 he observes $\gamma_{zt}^S > \gamma_{zt}^C$, and actual switching is decided trough a Bernoulli trial with mean $\gamma_{zt}^S$. The converse holds true for firms of type $S$.

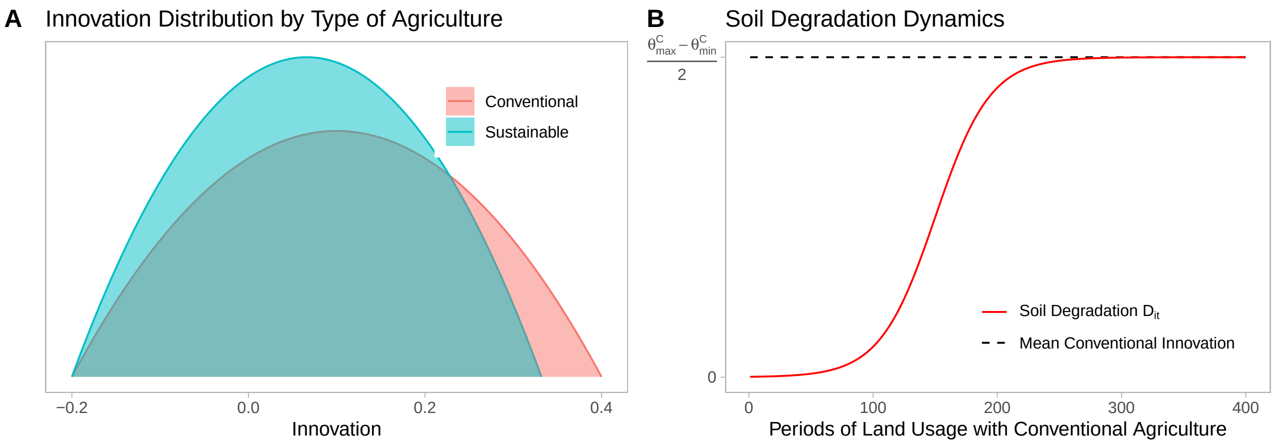


Figure B.1: Soil productivity dynamics in different agricultural regimes. Panel A: different innovation supports for conventional and sustainable farming. Panel B: graphic representation of soil degradation mechanism.

# C Calibration

Table C.1: Baseline parametrization of the model.

| Parameter Description | Symbol | Value |
|---|---|---|
| Labor Share | $\alpha$ | 0.8 |
| Max Share of Wealth to Hire Workers | $\zeta$ | 0.7 |
| Labor Sensitivity to Unfilled Demand | $\epsilon_L$ | 0.3 |
| Price Sensitivity to Excess Demand | $\epsilon_P$ | 0.02 |
| Maximum Labor per Cell | $L_{max}$ | 0.5 |
| Replicator Dynamics Intensity | $\epsilon_{MS}$ | 0.5 |
| Cost Weight in Fitness | $\omega_1$ | 0.05 |
| Rental Price of Land Weight in Fitness | $\omega_2$ | 0.05 |
| Unfilled Demand Weight in Fitness | $\omega_F$ | 1 - $\omega_1$ |
| Demand Growth | $\Delta_D$ | 4 |
| Demand Shock Variance | $\sigma_D$ | 0.01 |
| Fraction of Revenues to Innovation Expenditures | $r^{IN}$ | 0.1 |
| Fraction of Revenues to Imitation Expenditures | $r^{IM}$ | 0.05 |
| Innovation Lower Bound | $\theta_{min}$ | -0.2 |
| Innovation Upper Bound | $\theta_{max}$ | 0.4 |
| Innovation/Imitation Sensitivity to Innovation/Imitation Expenditure | $\iota$ | 2 |
| Ray of Observation for Imitation | dî | 1 |
| Fraction of Imitated Cell Productivity to Own Soil Productivity | $\mu_{IM}$ | 0.01 |
| Fraction of Leading Cell Productivity to Own Soil Productivity in within-firm Learning | $\mu_{IM}$ | 0.01 |
| Bidding Sensitivity to Spatial Distance | $\epsilon_A$ | 0.3 |
| Fraction of Wealth Bid Amount | $\Xi$ | 0.1 |
| Unfilled Demand Time Window when Bidding | $s^u$ | 5 |
| Rental Price of Land Shock Variance | $\sigma_r$ | 0.05 |
| Virgin Land Productivity Gain | $\Delta^f$ | 0.05 |
| Time to Reforest | $T^f$ | 50 |
| Deforesting Sensitivity to Unfilled Demand | $\epsilon_f$ | 0.1 |
| Ray of Observation when Switching Agricultural Regime | $d^s$ | 2 |
| Switching Intensity | $\tau$ | 1 |
| Switching Time Window | $q$ | 30 |
| Memory when Switching Agricultural Regime | $m$ | 30 |
| Soil Degradation Lower Asymptote | $A$ | 0 |
| Soil Degradation Upper Asymptote | $K$ | 0.1 |
| Soil Degradation Speed | $b$ | 0.045 |
| Soil Degradation Lateness | $M$ | 170 |

Table C.2: Baseline initialization of the model.

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

# D Additional tables

Table D.1: Summary statistics for baseline model, 500 Monte Carlo. Monte Carlo standard errors between parenthesis.

| | Excess Demand (%) | Food Price (% Initial-Final Change) | Bankrupts (% of Initial Firms) | Mean Output Growth (%) | Land Productivity (Inital Final Correlation) |
|---|---|---|---|---|---|
| MC Mean | -0.12 | -0.92 | 11.17 | 0.31 | 0.71 |
| MC SE | *(0.01)* | *(0.06)* | *(0.1)* | *(<0.01)* | *(<0.01)* |

Table D.2: Summary statistics for different spatial scenarios of initial land productivity. See Figure 6 for spatial scenarios. 50 Monte Carlo replications. Normalized Monte Carlo standard errors within parenthesis. Productivity mean and standard deviation normalized with respect to baseline. Baseline values highlighted in red. p-values significance codes for T-test for mean difference with respect to baseline (independent samples, unequal variances): *** $\leq 0.001$, ** $\leq 0.01$, * $\leq 0.05$, . $\leq 0.1$.

| | **Mean Excess Demand** (%, MC Mean) | **Food Price Change** (%, Initial Final Change, MC Mean) | **Mean Final Productivity** (Baseline=1, MC Mean) | **Final Productivity Standard Deviation** (Baseline = 1, MC Mean) |
|---|---|---|---|---|
| Two Clusters | -0.01* | -0.11* | 0.97*** | 1.32*** |
| | *(0.02)* | *(0.19)* | *(0.83)* | *(0.89)* |
| Four Clusters | -0.06 | -0.44 | 0.97*** | 1.33*** |
| | *(0.03)* | *(0.2)* | *(0.92)* | *(1.03)* |
| Six Clusters | -0.09 | -0.67 | 0.96*** | 1.3*** |
| | *(0.02)* | *(0.19)* | *(0.86)* | *(1.06)* |
| Random | -0.1 | -0.78 | 1 | 1 |
| | *(0.02)* | *(0.2)* | *(1)* | *(1)* |

Table D.3: Summary statistics with deforestation and land abandonment, and without (baseline). 50 Monte Carlo replications. Normalized Monte Carlo standard errors within parenthesis. Productivity mean and standard deviation normalized with respect to baseline. Baseline values highlighted in red. p-values significance codes for T-test for mean difference with respect to baseline (independent samples, unequal variances): *** $\leq 0.001$, ** $\leq 0.01$, * $\leq 0.05$, . $\leq 0.1$.

| | **Mean Excess Demand** (%, MC Mean) | **Food Price Change** (%, Initial Final Change, MC Mean) | **Mean Final Productivity** (Baseline=1, MC Mean) | **Final Productivity Standard Deviation** (Baseline = 1, MC Mean) |
|---|---|---|---|---|
| Baseline | -0.1 | -0.78 | 1 | 1 |
| | *(0.02)* | *(0.2)* | *(1)* | *(1)* |
| Deforestation | -0.1 | -0.78 | 0.98*** | 1.01 |
| | *(0.02)* | *(0.16)* | *(0.69)* | *(1.18)* |

Table D.4: Summary statistics for different levels of imitation, within-firm learning and replicator dynamics intensity. Replicator dynamics intensity $\epsilon_{MS}$ values: low $\epsilon_{MS} = 0.2$, baseline $\epsilon_{MS} = 0.5$, high $\epsilon_{MS} = 0.8$. 50 Monte Carlo replications. Monte Carlo standard errors within parenthesis. Productivity mean and standard deviation normalized with respect to baseline. Baseline values highlighted in red. p-values significance codes for T-test for mean difference with respect to baseline (independent samples, unequal variances): *** $\leq 0.001$, ** $\leq 0.01$, * $\leq 0.05$, . $\leq 0.1$.

**Mean Excess Demand (%, MC Mean)**

LOW Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.16*** | 0.01** |
| | *(0.03)* | *(0.03)* |
| Imitation ON | -0.1 | -0.15 |
| | *(0.02)* | *(0.02)* |

BASELINE Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.32*** | 0.03*** |
| | *(0.05)* | *(0.03)* |
| Imitation ON | -0.07 | -0.1 |
| | *(0.02)* | *(0.02)* |

HIGH Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.32*** | 0.07*** |
| | *(0.05)* | *(0.03)* |
| Imitation ON | -0.07 | -0.09 |
| | *(0.02)* | *(0.02)* |

**Food Price Change (%, Initial Final Change, MC Mean)**

LOW Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 1.31*** | 0.1** |
| | *(0.28)* | *(0.21)* |
| Imitation ON | -0.79 | -1.22 |
| | *(0.16)* | *(0.18)* |

BASELINE Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 2.66*** | 0.25*** |
| | *(0.39)* | *(0.22)* |
| Imitation ON | -0.5 | -0.78 |
| | *(0.19)* | *(0.2)* |

HIGH Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 2.62*** | 0.57*** |
| | *(0.38)* | *(0.23)* |
| Imitation ON | -0.5 | -0.72 |
| | *(0.18)* | *(0.19)* |

**Mean Final Productivity (Baseline=1, MC Mean)**

LOW Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.71*** | 0.84*** |
| | *(0.76)* | *(0.82)* |
| Imitation ON | 1.01 | 1.03*** |
| | *(0.98)* | *(0.99)* |

BASELINE Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.66*** | 0.86*** |
| | *(0.95)* | *(0.76)* |
| Imitation ON | 0.92*** | 1 |
| | *(1.01)* | *(1)* |

HIGH Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 0.66*** | 0.87*** |
| | *(0.87)* | *(0.9)* |
| Imitation ON | 0.92*** | 1 |
| | *(0.94)* | *(0.69)* |

**Final Productivity Standard Deviation (Baseline=1, MC Mean)**

LOW Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 2.91*** | 1.72*** |
| | *(0.95)* | *(0.91)* |
| Imitation ON | 1.38*** | 0.95* |
| | *(1.55)* | *(1.24)* |

BASELINE Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 3.22*** | 1.52*** |
| | *(0.9)* | *(0.95)* |
| Imitation ON | 2.09*** | 1 |
| | *(1.75)* | *(1)* |

HIGH Replicator Dynamics

| | within-firm Learning OFF | within-firm Learning ON |
|---|---|---|
| Imitation OFF | 3.11*** | 1.46*** |
| | *(0.87)* | *(1.01)* |
| Imitation ON | 2.12*** | 1.01 |
| | *(1.36)* | *(0.93)* |

Table D.5: Summary statistics for different values of imitation and within-firm learning intensity.

**Mean Excess Demand (%, MC Mean)**

| | -50% Imitation | -25% Imitation | Baseline Imitation | +25% Imitation | +50% Imitation |
|---|---|---|---|---|---|
| -50% within-firm Learning | -0.07 | -0.09 | -0.12 | -0.1 | -0.15 |
| | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* |
| -25% within-firm Learning | -0.08 | -0.09 | -0.11 | -0.15 | -0.13 |
| | *(0.02)* | *(0.02)* | *(0.03)* | *(0.02)* | *(0.02)* |
| Baseline within-firm Learning | -0.05 | -0.12 | -0.1 | -0.13 | -0.15 |
| | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* |
| +25% within-firm Learning | -0.1 | -0.04. | -0.12 | -0.17* | -0.15 |
| | *(0.02)* | *(0.03)* | *(0.02)* | *(0.02)* | *(0.02)* |
| +50% within-firm Learning | -0.04. | -0.14 | -0.13 | -0.15 | -0.14 |
| | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* |

**Food Price Change (%, Initial Final Change, MC Mean)**

| | -50% Imitation | -25% Imitation | Baseline Imitation | +25% Imitation | +50% Imitation |
|---|---|---|---|---|---|
| -50% within-firm Learning | -0.57 | -0.69 | -0.91 | -0.79 | -1.14 |
| | *(0.19)* | *(0.19)* | *(0.18)* | *(0.15)* | *(0.19)* |
| -25% within-firm Learning | -0.64 | -0.71 | -0.88 | -1.2 | -0.99 |
| | *(0.19)* | *(0.16)* | *(0.21)* | *(0.19)* | *(0.18)* |
| Baseline within-firm Learning | -0.39 | -0.91 | -0.78 | -1 | -1.2 |
| | *(0.17)* | *(0.19)* | *(0.2)* | *(0.16)* | *(0.17)* |
| +25% within-firm Learning | -0.75 | -0.27. | -0.96 | -1.34* | -1.18 |
| | *(0.13)* | *(0.22)* | *(0.17)* | *(0.18)* | *(0.17)* |
| +50% within-firm Learning | -0.32. | -1.08 | -1.04 | -1.18 | -1.11 |
| | *(0.18)* | *(0.19)* | *(0.15)* | *(0.15)* | *(0.18)* |

**Mean Final Productivity (Baseline=1, MC Mean)**

| | -50% Imitation | -25% Imitation | Baseline Imitation | +25% Imitation | +50% Imitation |
|---|---|---|---|---|---|
| -50% within-firm Learning | 0.92*** | 0.95*** | 0.98** | 1.01* | 1.03*** |
| | *-1* | *(0.78)* | *(0.76)* | *(0.85)* | *(0.8)* |
| -25% within-firm Learning | 0.93*** | 0.96*** | 0.99 | 1.01* | 1.04*** |
| | *(0.98)* | *(0.7)* | *(0.78)* | *(0.87)* | *(0.88)* |
| Baseline within-firm Learning | 0.93*** | 0.96*** | 1 | 1.02** | 1.04*** |
| | *(0.77)* | *(0.68)* | *(1)* | *(0.73)* | *(0.75)* |
| +25% within-firm Learning | 0.94*** | 0.97*** | 1 | 1.02*** | 1.05*** |
| | *(0.8)* | *(0.97)* | *(0.89)* | *(0.74)* | *(0.6)* |
| +50% within-firm Learning | 0.95*** | 0.97*** | 1 | 1.02*** | 1.05*** |
| | *(0.75)* | *(0.72)* | *(0.68)* | *(0.64)* | *(1.03)* |

**Mean Final Productivity (Baseline=1, MC Mean) Final Productivity Standard Deviation (Baseline=1, MC Mean)**

| | -50% Imitation | -25% Imitation | Baseline Imitation | +25% Imitation | +50% Imitation |
|---|---|---|---|---|---|
| -50% within-firm Learning | 1.29*** | 1.16*** | 1.07*** | 1 | 0.93** |
| | *(0.85)* | *(0.83)* | *(1.09)* | *(0.97)* | *(1.21)* |
| -25% within-firm Learning | 1.26*** | 1.12*** | 1.03 | 0.95* | 0.92*** |
| | *(0.93)* | *(0.8)* | *(1.04)* | *(1.01)* | *(1.08)* |
| Baseline within-firm Learning | 1.22*** | 1.09*** | 1 | 0.93*** | 0.89*** |
| | *(1.04)* | *(0.97)* | *(1)* | *(1.02)* | *(0.97)* |
| +25% within-firm Learning | 1.22*** | 1.11*** | 0.98 | 0.91*** | 0.85*** |
| | *(0.83)* | *(0.93)* | *(0.89)* | *(0.87)* | *(1.06)* |
| +50% within-firm Learning | 1.21*** | 1.1*** | 1 | 0.89*** | 0.84*** |
| | *(1.11)* | *(0.95)* | *(0.85)* | *(1.01)* | *(1.21)* |

*Note:* Normalized Monte Carlo standard errors within parenthesis. Productivity mean and standard deviation normalized with respect to baseline. Baseline values highlighted in red. p-values significance codes for T-test for mean difference with respect to baseline (independent samples, unequal variances): *** $\leq 0.001$, ** $\leq 0.01$, * $\leq 0.05$, . $\leq 0.1$.

Table D.6: Percentage differences of both cumulative output and land productivity with respect to the baseline unshocked model, for the three shocked cells.

**Most Productive Farm**

| | *Output* | | | | | *Land Productivity* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 |
| $t_0 + 5$ | -4.27*** | -1.17** | -0.73 | 0.1 | -0.01 | -0.08 | 0.06 | -0.06 | -0.02 | 0.01 |
| $t_0 + 10$ | -3.53*** | -1.05* | -0.72 | 0.06 | 0 | -0.14 | 0.07 | -0.07 | -0.02 | 0.01 |
| $t_0 + 20$ | -2.99** | -0.84 | -0.4 | 0.13 | -0.04 | -0.06 | 0.13 | -0.13 | -0.05 | 0.04 |
| $t_0 + 50$ | -3.31* | -0.66 | 0.08 | 0.26 | -0.12 | -0.23 | 0.26 | -0.13 | 0.04 | 0.07 |
| $t_0 + 100$ | -4.23* | -0.66 | 0.03 | 0.14 | 0.09 | -0.72. | 0.27 | -0.05 | 0.15 | 0.12 |
| $t_0 + 200$ (End) | -4.64. | -2.77 | -0.06 | 0.75 | 0 | -1.01* | -0.09 | 0.28 | 0.35. | 0.24 |

**Median Farm**

| | *Output* | | | | | *Land Productivity* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 |
| $t_0 + 5$ | -4.69*** | -1.27*** | -0.34* | -0.03 | 0.04 | -0.03 | -0.05 | 0.01 | 0.01 | -0.02 |
| $t_0 + 10$ | -4.76*** | -1.09** | -0.16 | 0.06 | 0.01 | -0.13 | -0.06 | 0.04 | 0.02 | -0.04 |
| $t_0 + 20$ | -5*** | -1.11* | -0.18 | 0.12 | -0.05 | -0.33 | -0.11 | 0.02 | -0.02 | -0.04 |
| $t_0 + 50$ | -4.79** | -1 | -0.31 | 0.13 | -0.1 | -0.59. | -0.18 | 0 | -0.06 | 0.01 |
| $t_0 + 100$ | -5.84** | -0.95 | -0.44 | 0.12 | 0 | -0.91* | -0.27 | -0.01 | -0.12 | 0.03 |
| $t_0 + 200$ (End) | -5.98* | -0.94 | -0.12 | -0.17 | 0.11 | -0.91 | -0.29 | -0.13 | -0.11 | -0.05 |

**Least Productive Farm**

| | *Output* | | | | | *Land Productivity* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 | Epicenter | Ray 1 | Ray 2 | Ray 3 | Ray 4 |
| $t_0 + 5$ | -3.19*** | -1.25*** | -0.34* | -0.08 | -0.13 | 0.13 | -0.01 | 0.01 | 0 | 0.02 |
| $t_0 + 10$ | -1.49* | -1.13*** | -0.3 | -0.03 | -0.18 | 0.23 | -0.04 | 0.02 | -0.04 | 0.04 |
| $t_0 + 20$ | -1.22 | -1.07* | -0.3 | -0.02 | -0.2 | 0.19 | -0.07 | 0.04 | -0.08 | 0.07 |
| $t_0 + 50$ | -1.95 | -1.18 | -0.2 | 0.08 | -0.48 | -0.09 | -0.18 | 0.05 | -0.03 | 0.05 |
| $t_0 + 100$ | -4.33 | -1.48 | 0.27 | 0.18 | -0.35 | -1.23 | -0.27. | 0.15 | 0.15 | 0.1 |
| $t_0 + 200$ (End) | -7.95 | -2.15 | -0.16 | 0.62 | 0.33 | -3.36 | -0.56* | 0.14 | 0.3 | 0.17 |

*Note:* Observations are averaged across Monte Carlo replications and across distances with respect to the epicenter. 50 Monte Carlo replications. p-values significance codes for T-test for mean difference with respect to baseline (independent samples, unequal variances): $^{***} \leq 0.001$, $^{**} \leq 0.01$, $^{*} \leq 0.05$, $. \leq 0.1$.

# E Additional figures

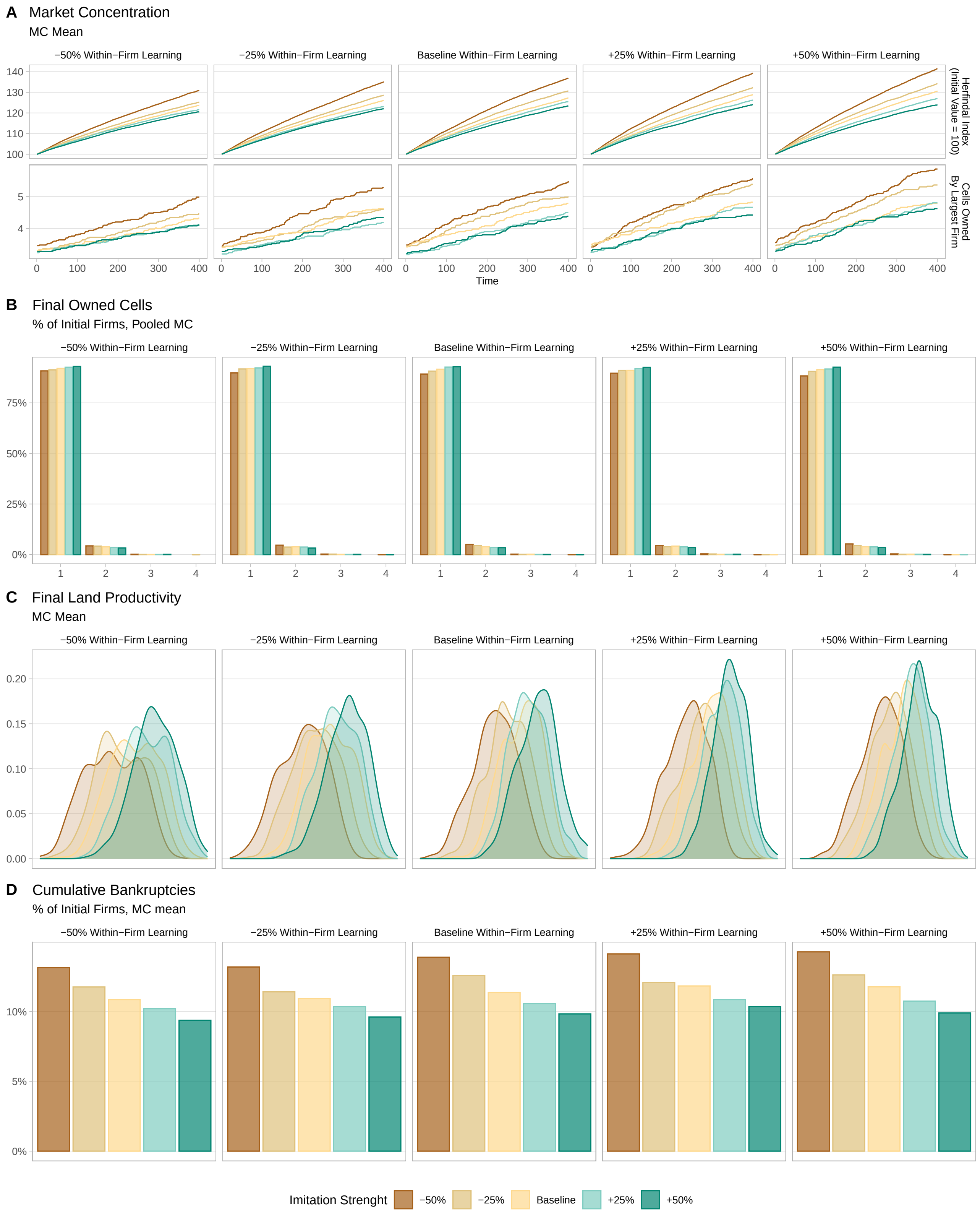


Figure E.1: Market and land concentration, land productivity and bankruptcies for different values of imitation and within-firm learning intensity. 50 Monte Carlo replications.