Food Policy 111 (2022) 102304

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Impact of climate smart agriculture on food security: An agent-based analysis

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ARTICLE INFO

JEL classification:
C63
O13
Q1
Q15
Q55
Q56

Keywords:
Climate smart agriculture
Food security
Agent-based modelling
Externality
Sustainable development

ABSTRACT

The study proposes an agent-based model to investigate how adoption of climate smart agriculture (CSA) affects food security. The analysis investigates the role of social and ecological pressures (i.e. community network, climate change and environmental externalities) on the adoption of physical water and soil practices as well as crop rotation techniques in rural Ethiopia. The findings reveal that CSA can be an effective strategy to improve the rural populations' well-being for farm households with access to capital, strong social networks and access to integrated food markets. The climate scenario simulations indicate that farmers adopting CSA fare better than non-adopters, although CSA adoption does not fully counterbalance the severe climate pressures. In addition, farmers with poor connections to food markets benefit less from CSA due to stronger price oscillations. These results call for an active role for policy makers in encouraging adaptation through CSA adoption by increasing access to capital, improving food market integration and building information sharing among farmers.

1. Introduction

As the world grapples with the potential problems created by global climate change a great deal of analysis has turned toward considering adaptation possibilities, especially for farmers in poor countries. One such adaptation which has shown promise in the developing world and garnered a lot of recent academic interest is climate smart agriculture (CSA) (Amadu et al., 2020; Marenya et al., 2020; Tesfaye et al., 2020). Climate smart agriculture is a package of micro-level soil and water conservation improvements such as planting and agroforestry techniques that can help farmers adapt to climate change. A number of recent papers have shown the current effectiveness and in some cases willingness of farmers to adopt CSA techniques in such places as Ethiopia, Peru, and Malawi (Amadu et al., 2020; Marenya et al., 2020; Tesfaye et al., 2020). While this literature shows CSA adoption under current circumstances, understanding longer term adaptation to climate change requires understanding the dynamics and effectiveness of this adaptation strategy over time and into the future. Specifically, the literature on technology adoption has shown the importance of learning by doing and learning from neighbours (Bramoullé and Kranton, 2016; Conley and Udry, 2010), and the potential failure of some technologies as the current climate changes. An accurate assessment of the ability of CSA techniques to help developing country farmers adapt to climate change requires modelling both adoption paths and future climate dynamics. How will the future dynamics of climate and farmer social interactions determine climate smart agriculture's success or failure in improving food security?

Answering such a question requires moving beyond current econometric approaches, which take past data as the guide to future farmer adaptation behavior. While this provides well identified answers for the current state of knowledge and climate, projecting into the future from such work requires strong assumptions on the static nature of adaptation, farmer behavior, and farmer networks. Our work innovates on the adaptation literature by using an agent-based modelling (ABM) approach to understand farmer adoption of CSA innovations in rural Ethiopia while facing current and future climate change. Such a

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https://doi.org/10.1016/j.foodpol.2022.102304
Received 4 June 2021; Received in revised form 5 June 2022; Accepted 20 June 2022
Available online 28 June 2022
0306-9192/

forward-looking modelling exercise allows us to generate an understanding of future adaptation dynamics, in which the agents themselves learn, choose, and adapt to a changing climate dealing with uncertainty (Berger et al, 2017). Understanding such future adaptation dynamics is fundamental to helping current policy makers make forward looking choices for how to promote climate adaptation.

To contextualise the analysis, we initialize the model to the adoption rate of climate smart agriculture practices and soil fertility derived from farm survey data in the lowland and valley fragmented agroecosystem of Ethiopia's Choke mountain watershed (Simane et al., 2013). We choose this region because historically it is capable of registering surplus agricultural production, but also suffers from serious land and water resource degradation which may produce food shortages especially as the climate changes (Zaitchik et al., 2012; Teferi et al., 2013). In addition, it is the major production zone for Ethiopia's national crop, tef (Simane et al., 2013).

This work brings a novel modeling approach to the study of CSA adoption and farmer climate adaptation. Agent based models (ABM) develop a computational approach able to study complex socio-economic systems characterised by different degrees of organisation and to interpret the interaction between heterogeneous agents who can have complex and non-linear behaviours. ABMs allow us to model agents that may have different information sets and behave according to rules derived from empirical data or laboratory experiments thereby enhancing the realism of the analysis (Tesfatsion and Judd, 2006; Branch and Evans, 2006). Adopting an iterative bottom-up approach and agents' adaptive learning process (Delli Gatti et al., 2011), ABMs allow us to investigate system dynamics endogenously generated within the model while taking into account the possible redistributive implications. This bottom up approach with endogenously determined system dynamics allows for a more comprehensive policy assessment for future climate adaptation. Like the standard micro-econometric approach to CSA adoption, ABMs focus on the behavior of individual actors faced with economic and information incentives. Unlike micro-econometric approaches, the ABM allows us to simulate future scenarios and endogenous interactions between individuals, which is vital for understanding adaptation to future climate change.

Our ABM incorporates agent interactions in peer-to-peer networks, recognizing that human cognition and management ability is itself a scarce resource and depends on environmental and cultural context, incentives, and past experiences (Conlisk,1996; Duffy, 2006). The agents in our ABM represent a range of autonomous farmers who have dynamic behaviours and heterogeneous characteristics (Heckbert et al., 2010; An, 2012; Dobbie et al., 2018). Agents interact with each other according to social and ecological pressures, resulting in emergent macro-scale outcomes that can be used to study the whole system through scenario analyses (Smajgl et al., 2011; Bazzana et al., 2021).

According to Adesina and Zinnah (1993) and Ngwira et al. (2014), CSA practice adoption is affected by the farmer's perceptions of these technologies, as much as the characteristics of the technologies themselves. Smallholder farmers have subjective preferences for characteristics of CSA techniques which may also be affected by their social context. For these reasons, we take into account farmers' neighbours adoption, their social interactions, and their impact on the rate of adoption of different types of CSA techniques. With our ABM modeling we also distinguish between short and long-term practices, which can have different dynamics.

The objective of this study is to investigate whether CSA adoption dynamics positively affect the food security of households. In line with the Food and Agriculture Organization of the United Nations (FAO, 2021), we use a multidimensional definition of the food security accounting for: food availability, food self-sufficiency, food instability, and food insecurity severity. Because they may produce different dynamics, all four dimensions are important in analysing the effectiveness of CSA adoption and adaptation to future climate change.

In order to provide input into how policy makers might influence the climate adaptation process, the ABM allows us to explicitly investigate multiple channels that can impact the adoption and food security impacts of CSA. The variations in channels of impact we investigate are social networks, market integration, and drastic climate change. The ABM explicitly models the role of social networks (participation in community activities) in changing the adoption of CSA strategies that reduce farmers' food insecurity. More precisely, we compare the system dynamics of a baseline scenario with two scenarios with higher and lower social network participation rates. In addition, we extend the analysis by exploring the adaptive responses to the surrounding market integration characteristics (Williams et al., 2020) by altering the price transmission mechanism, i.e., varying market conditions generated by geography and remoteness, which affects the market price dynamics of the food commodities and local wealth. A final enquiry expands the analysis by comparing the baseline scenario to a case in which climate change is more dramatic. The aim of this analysis is to investigate from a food security perspective, whether CSA is an effective mitigation strategy for drastic climate change that increases the vulnerability of farmers to production risk.

Our agent-based modelling of CSA adoption investigates the importance of key policy relevant parameters for adaptation to climate change: social networks, the workings of food markets in price transmission, and the severity of future climate change to farmers' abilities to adapt and their concomitant food security outcomes. It provides a proof of concept for how researchers and policy makers can think about and analyze farmer adaptation to future climate change in developing countries where agriculture is characterized by small-holder subsistence farming. In particular, it demonstrates how common features of micro-econometric models, networks and adoption dynamics, can be modeled in a future oriented ABM to show how policy makers can leverage these features to affect future farmer adaptation to climate change. The big advantage of an ABM for future policy analysis is that the scenarios allow the individual farmers to choose their own adaptation paths. Moreover, the methodological framework is sufficiently flexible and general that, changing the data source used for the initialization and the parametrization, it can be implemented to investigate CSA innovation adoption and its effect on food security in other geographical contexts.

The remainder of the paper is structured as follows: Section 2 presents the methodological approach. In Sections 2.1 and 2.2 are presented the overview of the model and the sequence of the events. Section 2.3 describes the willingness to adopt innovations and the actual CSA adoption; Sections 2.4 and 2.5 define the supply and demand side of the food commodities, whereas Section 2.6 presents the aggregate variables. Section 2.7 concludes with the scenario description and the simulation parameters. Section 3 describes the simulation results: in Section 3.1 are shown the aggregated effects of CSA adoption, Sections 3.2 and 3.3 show the impact of the social network and the market access to the adoption rate and the food demand satisfaction, Section 3.4 investigates the effectiveness of CSA in managing drastic climate change, whereas in Section 3.5 we perform some robustness analysis. Sections 4 and 5 close with policy suggestions and concluding remarks.

2. Methodological approach

2.1. Overview

The model represents a stylized small agricultural community living in a village in Africa and choosing CSA practices. We calibrate the model itself to data from villages in northwest Ethiopia. The basic structure of the agent based modelling system considers a population of small-holder subsistence farmers ($j = 1, \cdots, J$) characterized according to age, social network participation, land size (H), and economic endowment (M). The household sector consists of farmers who may work in their own fields or supply labour to the other farmers within the village boundaries. Farmers have limitations in their ability to process new information,

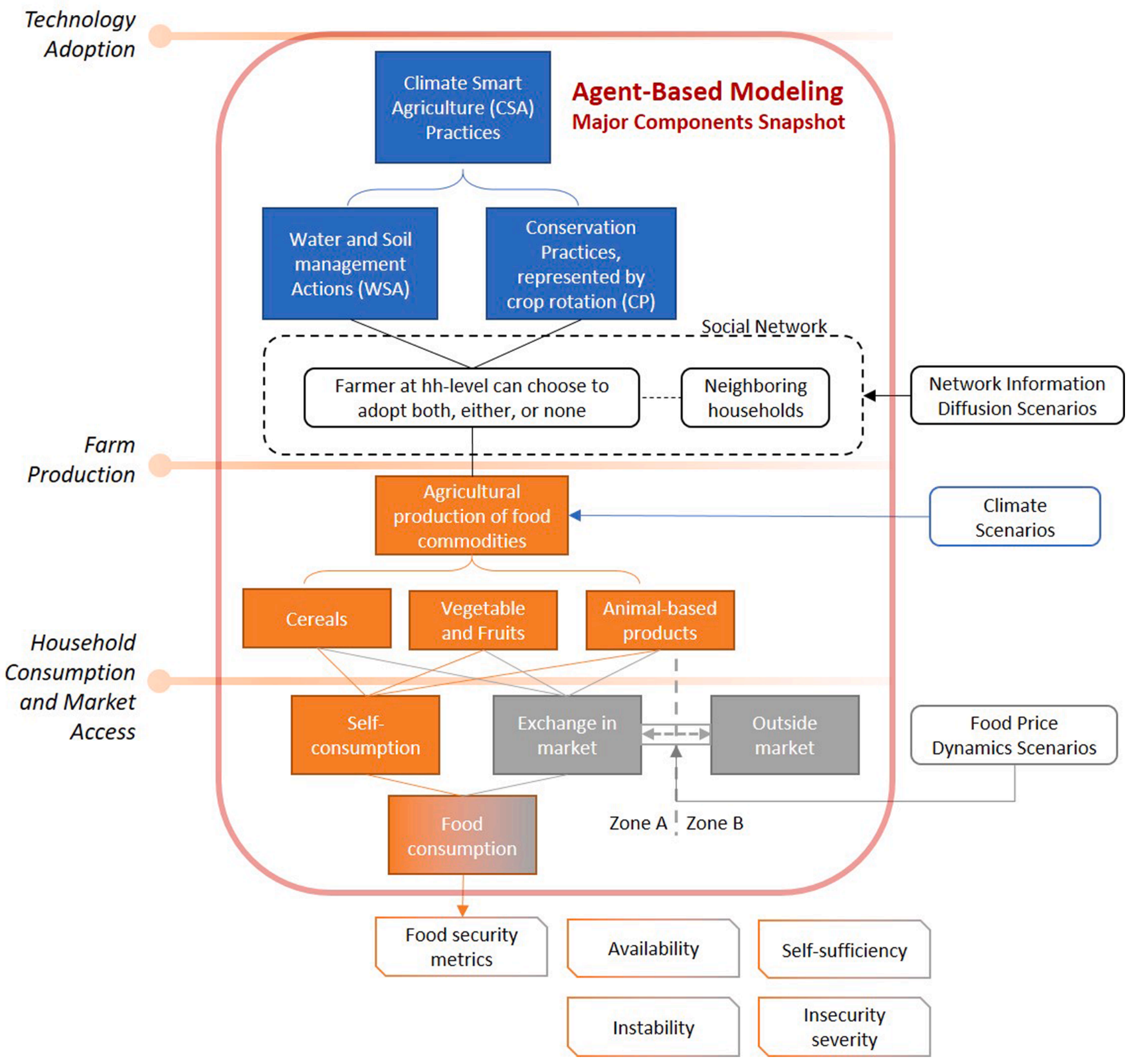

Fig. 1. Flow chart of the methodology. This flowchart shows the major components and how they are linked in our agent-based model. The model simulates farmers' decision-making on technology adoption of CSA practices, adapting both, either or none of the two general categories of WSA and CP. Their decisions are affected by participating in social networks, affecting farm productions and the subsequent household consumption. Households also have access to markets for selling and purchasing food products, which affects their available economic resources and food consumption. The model outcomes are measured by four food security metrics, including availability, self-sufficiency, instability, and food insecurity severity (see Section 2.6). The model is run under scenarios that differ in network information diffusion extents, food price dynamics in integrated or non-integrate markets, and climate conditions.

based on differences in human, physical, and social capital, i.e,. they are not perfectly rational and have heterogeneous management abilities. Specifically, they differ in available land, land productivity, financial resources, family size and age of the household head, participation in social networks and initial CSA technique adoption choices.

In each period ($t = 1, \cdots, T$), the households perform the following activities: 1) decide whether to adopt long and/or short term CSA practices, 2) cultivate land using production input as farmers, 3) supply labour to the local labour market, 4) consume food commodities ($i = 1, \cdots, I$), and 5) exchange agricultural products on the market (Fig. 1). We assume that farmers have information processing limitations and live in an incomplete and asymmetric information context; thus, they are boundedly rational and follow simple rules of behaviour.

2.2. Sequence of events

The economy is an iterative system where agents repeat the same group of actions at each time step. First of all, agents decide whether to adopt CSA practices. Farmers who are members of a social network may randomly meet another community member. If the farmers meet, they modify positively/negatively their WSA/CP adoption probability based on the new information gained from their fellow farmers' experiences.

Based on the expectation on climate variables, productivity and farmer's type (degree of innovativeness), farmers set their land use and desired production inputs. Output depends on farmers' financial constraints, rainfall during the production period, and neighbour's soil and water practices (positive or negative externalities). According to the household's composition, the farmer computes its food security requirement. If production is higher than self-consumption demand, the farm household consumes their own food commodities and sells on the market the surplus. In the opposite case, households access the market to satisfy their household food requirements.

At the end of the period, the household members become one period older, except for those who die. Hence, the household's size evolves according to the difference between mortality and birth rate. Births are distributed among households according to a uniform distribution whereas, to define the *j-th* household member who dies, we use a death

Table 1
Scenario parameters settings.

Scenario	Food Price Dynamics	Network	Representative Concentration Pathway[1]
A (Baseline)	Exogenous	60%	4.5
B	Exogenous	75%	4.5
C	Exogenous	45%	4.5
D	Endogenous	60%	4.5
E	Exogenous	60%	8.5

[1] Representative Concentration Pathway (RCP) is a trajectory of greenhouse gas concentration into the future decades adopted by the climate modeling and research community. RCP is labeled using a range of radiative forcings in the year 2100. RCP 4.5 falls in the mid-range, representing an intermediate climate change scenario, while RCP 8.5 represents the worst-case scenario with high levels of greenhouse concentrations.

Table 2
Values of model parameters and initial conditions.

	Description	Value
Model Parameters		
J	Number of households	100
H	Maximum number of plots	20
σ	Discount factor	0.9
δ	Share of land affected by market driven mechanism	0.25
s	Share of income invested in the production process	0.95
g	Bias coefficient	1
z	Average family size	5
$\lambda_{WSA,Age}$	Ageing impact on WSA adoption propensity	0
$\lambda_{CP,Age}$	Ageing impact on CP adoption propensity	−0.012
$\lambda_{WSA,Network}$	Network impact on WSA adoption propensity	+0.65
$\lambda_{CP,Network}$	Network impact on CP adoption propensity	−0.45
	Irrigation service extension	30%
Initial Conditions		
A	Soil fertility range	0.95; 1.05
	Percentage of population adopting WSA	78%
	Percentage of population adopting CP	32%

probability drawn from a uniform distribution [0,1]. If this probability is lower than the household cohort death probability,[1] the farmer dies. In the opposite case, she survives. According to this mechanism, older agents have a higher probability of dying.

2.3. Climate smart agriculture practice adoption

The CSA practices include two main types: physical water and soil management actions (WSA), which have high costs and are a long time-pay back investment; and conservation practices (CP), such as no or minimum tillage, crop residue management, and crop rotation (Howden et al., 2007), which affect the crop yields in the short term and have relatively lower initial investment costs.

Following the literature we set the propensity to apply short/long term CSA practices to be driven by two main farmer attributes: social network memberships and the farmer's age (Di Falco et al., 2011; Ahmed, 2014; Tefera and Larra, 2016). The membership in the community network is assumed to create a higher exchange of information on the best practices or mitigation strategies to external climate shocks. Therefore, network information can affect the farmer's beliefs on the benefits of different CSA practices. Based on the survey data and results reported in Simane et al. (2013): additional network information reduces expectations on CP's impact on soil productivity and subsequently the adoption rate, whereas it has a positive effect on the belief about the benefits due to WSA on crop yields and would increase its adoption rate. In line with empirical studies from Ethiopia, Simane et al. (2013) and Wossen et al. (2013), the choice of crop rotation is negatively affected by farmer age whereas soil and water management actions does not depend on her age.

Farmer adoption depends on her belief (*bf*) of CSA adoption's effect on soil productivity which is updated in the following manner:

$$bf_{j,x,t} = bf_{j,x,t-1} + \lambda_{x,Age} + \lambda_{x,Network};$$

where $\lambda_{x,Age}$ and $\lambda_{x,Network}$ are negative when $x = CP$, whereas when $x = WSA$ they are zero and positive, respectively. If farmer j has positive beliefs about the benefits, $bf_{j,x,t} \geq 0$, the farmer is willing to adopt the *x-th* CSA practice (WSA and CP) in period t, whereas in the opposite case the farmer does not adopt it. We parameterize the λ's using data derived from the Simane et al. (2013) farm level survey of CSA adoption.

At the beginning of each year, the farmer with positive beliefs about the CSA practices decides whether to implement the respective practices. Given that WSA are long-term actions, which last for five periods, the farmer computes and compares the expected present value (U) of the economic return of the production types with and without the WSA implementation:

$$U_{x,t} = \sum\nolimits_{n=1}^{5} \sigma^n \left(p_{-x,t} Y_{-x,t} - \tau_{x,t} \right). \tag{2}$$

In equation (2), σ is the discount factor of the future economic returns; $\tau_{x,t}$ is a fixed adoption cost when $x = WSA$ (equal to zero in case of non-adoption, i.e., $x = NWSA$); $p_{-x,t}$ and $Y_{-x,t}$ are the average price and production over three food commodities (cereal, vegetable and fruits, and animal-based products) with/without soil and water management practices adoption at the time period t. The adoption of WSA increases crop yields, but has a cost, $\tau_{WSA,t}$, whereas if the farmer does not adopt WSA there is no gain in crop productivity and no adoption cost. Then, following standard random utility adoption models if $U_{WSA,t} \geq U_{NWSA,t}$, the farmer adopts WSA.

Farmers have heterogeneous expectations (E) on yields and climate variables, which evolve according to the following path dependent heuristic:

$$E_{j,t-1}\left(v_{j,t}\right) = g_j v_{j,t-1}; \tag{3}$$

with $g_j > 0$ representing a farmer-specific bias coefficient and v acting as the reference variable. The behavioural assumption is that farmers form their expectations on future climate variables using the last observed levels, and then adjusted with some bias factor (see Conlisk, 1996; Duffy, 2006; Nolan et al., 2009; Groeneveld et al., 2017). Farmers are optimistic (or pessimistic) about the reference variables if $g_j > 1$ (or $g_j < 1$), whereas if $g_j = 1$ the agents form their expectations only using the last observed level.

Once the farmer has decided on the adoption of WSA, she allocates the available land to food production. The farmer population can be divided into four different behaviour types: double adopters, WSA adopters, CP adopters and non-adopters. In line with Bazzana et al. (2021), farmers implementing crop rotation process cultivate the *h-th* plot as follows:

$$h_{i,t} = h_{i+1,t-1} \bigvee h_{i,t-1} = h_{i+1,t-2} \bigvee h_{i,t} \neq h_{i,t-2}; \tag{4}$$

where $i = 1{:}3$ represents the three different food crop production types (cereals, vegetables and fruits, and animal based products produced through grazing). We assume this type of crop rotation because it is

[1] See the Ethiopian life table for the cohort death probability (World Health Organization, 2018).

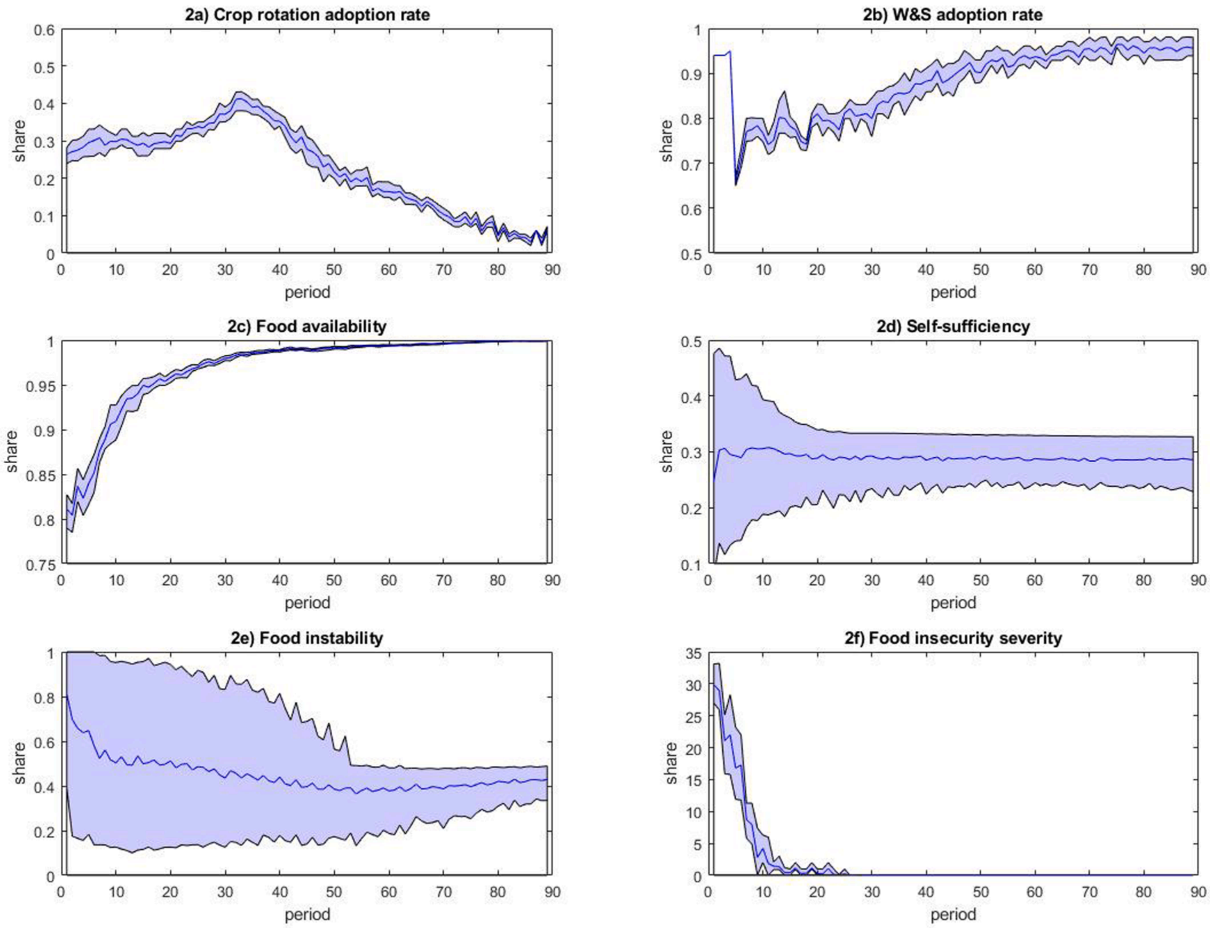

Fig. 2. CSA adoption and evolution of the food security dimensions. This figure shows the results from running 100 Monte Carlo simulations of the ABM using scenario A with our baseline information in a village of 100 households over a 90-year period. Fig. 2a and b show the share of adopters in the farmers population, who adopt the Climate Smart Agriculture technology, crop rotation or water and soil management action, respectively. Fig. 2c, d and e show the level of the respective food security metric - availability, self-sufficiency, and instability, whereas Fig. 2f shows the average number of households (share in the population) as defined in food insecurity severity. Given that we are running 100 Monte Carlo simulations for each of the 14 climate scenarios, the figures represent both the average level (in blue line) and the results between the 10th and the 90th percentile (with the half-transparent band).

typical of the region and optimal in highland Ethiopia in order to preserve soil productivity.

In contrast, farmers not adopting crop rotation primarily plant plots according to a “business as usual” rule with a market driven correction, i.e., they plant the same crop as the previous period, changing the allocation of land between crop types based on relative prices in the market. These farmers reallocate a share (δ) of the land from the lowest economic return crop in the previous period to the crop with the highest past economic return:

$$R_{j,i,t-1} = \frac{p_{i,t-1} Y_{j,i,t-1}}{K_{j,i,t-1}}. \tag{5}$$

In equation (5), $R_{j,i,t-1}$ is the economic return of the *i-th* agricultural production for the *j-th* farmer in the last period; $p_{i,t-1}$, $Y_{j,i,t-1}$ and $K_{j,i,t-1}$ are the price, the production and the land planted with the *i-th* commodity. To capture key features of subsistence farming, the available land for food crops that is not affected by the market driven mechanism will be cultivated as usual, i.e., with the same crop as in the past ($h_{i,t} = h_{i,t-1}$).

The decisions on land use and CSA practices will affect farm plot fertility ($A_{h,t}$) as follows:

$$A_{h,t} = \left(1 + \kappa_j + \eta_j + \eta_d\right) A_{h,t-1}; \tag{6}$$

where κ represents a discount (degradation) rate and η is the WSA effect on soil fertility. Hence, plot fertility for the *j-th* farmer is determined by her short and long-term agriculture practice choices (Holden et al., 2004). Continuous cropping reduces the plot productivity over time ($\kappa_j \leq 0$) whereas crop rotation is able to maintain the plot productivity ($\kappa_j = 0$). Moreover, land productivity is positively affected by the adoption of soil and water management practices by both the landowner ($\eta_j \geq 0$) and the farmers in the neighbouring plots ($\eta_d \geq 0$, positive externality).

2.4. *Farmer's production*

Based on their available income for farm production purposes ($M_{j,t-1}$), the farmers hire labour and purchase production inputs (fertilizers and seeds), and use irrigation water if they have access to an irrigation scheme, to produce the *i-th* food commodity in each plot (h). The agricultural food production function ($Q_{h,t}$) is defined according to a Leontief production functions with no substitution possibilities among the inputs:

$$Q_{i,h,t} = min\left(\frac{L_{i,h,t}}{a_{i,L}}, \frac{S_{i,h,t}}{a_{i,S}}\right); \tag{7}$$

where $L_{i,h,t}$ and $S_{i,h,t}$ represent labour quantities and the other representative production inputs, whereas a_L and a_S are the positive technologically determined parameters.

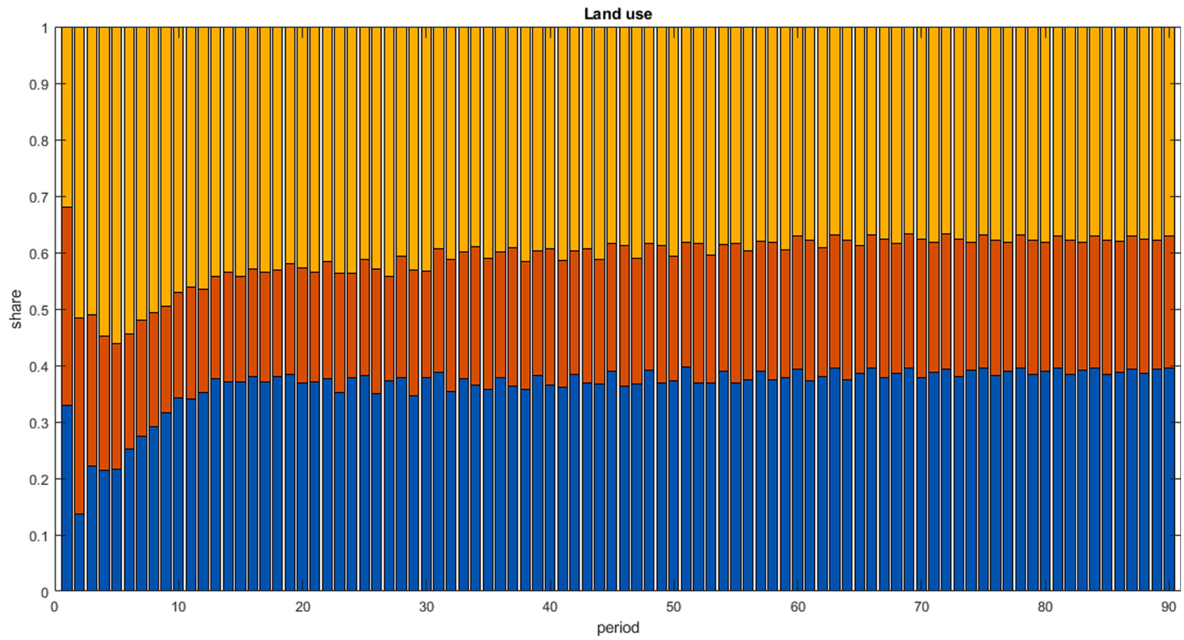

Fig. 3. Average land allocation among agricultural productions. This figure shows the average results from running 100 Monte Carlo simulations of the ABM using scenario A with our baseline information in a village of 100 households over a 90-year period. The y-axis is the share of total available land allocated to cereals (blue bars), vegetables and fruits (red bars), and pasture for animal-based food products (yellow bars). (For interpretation of the references to colour in this figure, the reader is referred to the web version of the article.).

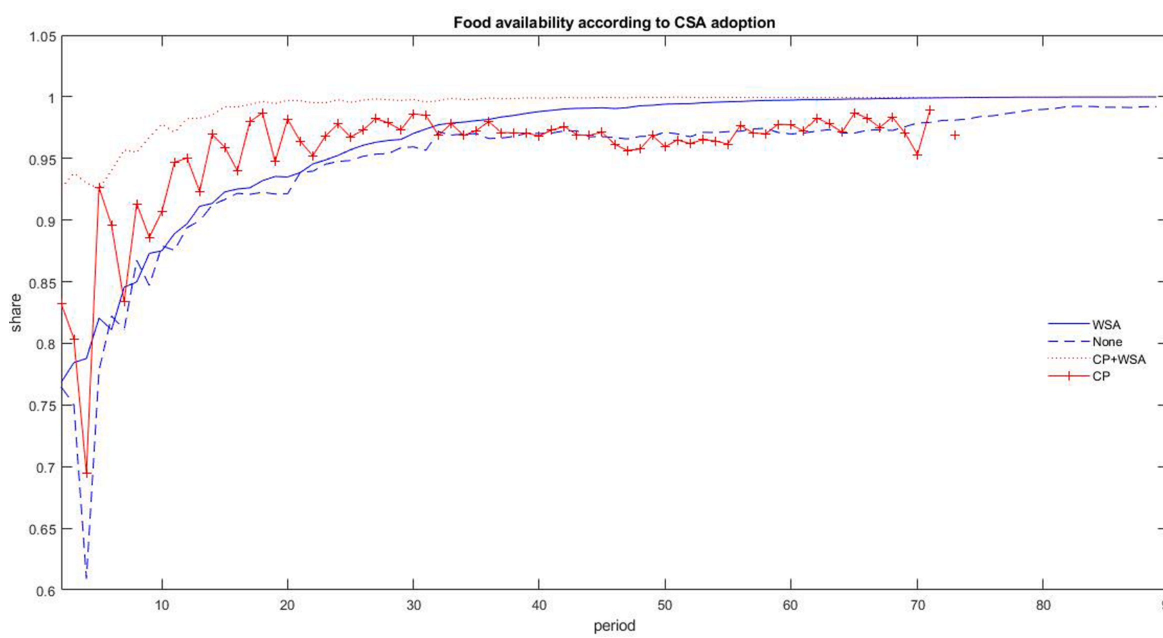

Fig. 4. Food availability evolution by CSA adoption. This figure shows the average results from running 100 Monte Carlo simulations of the ABM using scenario A with our baseline information in a village of 100 households over a 90-year period. The y-axis is the average level of food availability for the four types of farmers**.** double adopters (dotted line), WSA adopters (solid line), CP adopters (crossed line), non adopters (dashed line).

In making decisions on how to optimize the production process, the farmer is bounded by the following budget constraint:

$$w_t L_{i,h,t} + p_{s,t} S_{i,h,t} = \varsigma M_{j,t-1};$$

$$M_{j,t-1} = \left[\sum\nolimits_{i=1}^{3} \pi_{i,j,t-1} + w_t L_{j,t-1} + (1-\varsigma) M_{j,t-2} \right];$$

where w_t and $p_{s,t}$ are the price of labour and the other input;ς is the marginal propensity to save and $\varsigma M_{j,t-1}$ represents the available monetary resources from the previous periods which are the sum of past profits ($\pi_{i,j,t-1}$) from the production of the *i-th* commodity, labour income and savings.[2] The farmer hires outside workers if the optimal

[2] In line with the current state of credit markets in Ethiopia we assume farmers are credit constrained and have to finance investments based on their available savings.

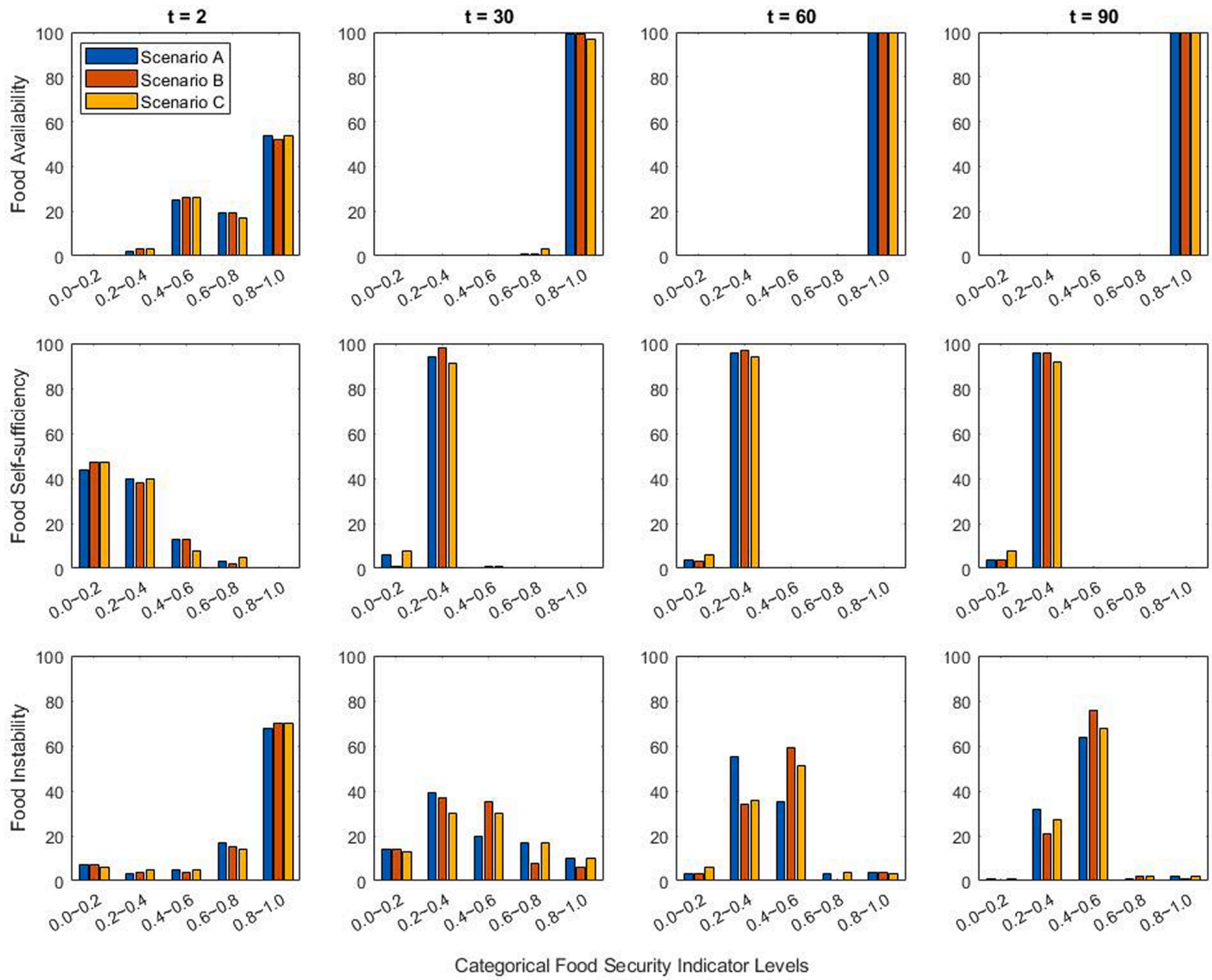

Fig. 5. Distribution of effects across households within a village. This figure shows the histogram of the food security indicators from running 100 Monte Carlo simulations using scenario A (social network extension 60%), scenario B (social network extension 75%), and scenario C (social network extension 45%). The y-axis is the number of households that fall into each of the bins defined in x-axis based on the level of the respective food security indicator. The first row represents food availability, the second row is self-sufficiency, and the third row shows food instability.

amount of labour required by the agricultural production process is higher than the farmer's household labour supply. In the opposite case, the household sells excess labour time to the other farmers in the village generating income.

In line with the empirical literature (Lobell and Burke, 2010), the actual crop yield ($Y_{h,t}$) depends on both the soil productivity ($A_{h,t}$) and the effects of available water (rainfall and irrigation) and air temperature (ρ):

$$Y_{h,t} = \rho_t A_{h,t} Q_{h,t};$$

where $0 \le \rho_t \le 1$ represents the water stress parameter. Following the analysis and parameterization in Block et al. (2008), $\rho_t = 1$ means that yields are not limited by water stress (*e.g.* if farmers have access to irrigation), although limitations by other factors such as soil fertility or management skills are still possible, while $\rho_t = 0$ implies crop destroying drought stress. The parameter ρ_t is computed for the study zone using a process-based soil–water balance model as described in Zhang et al. (2020). The model simulates soil moisture variation and crop growth in gridded soil columns using daily climate variables (rainfall and air temperature), irrigation if any, water holding capacities of the soil, and crop-specific characteristics (such as crop calendars and drought resistant features), and computes a yield factor (i.e., the water stress parameter ρ_t) for the entire growing period.

2.5. Households basic needs satisfaction

According to the family size, the total food requirements ($C_{-j,i,t}$) are defined as follows:

$$C_{-j,i,t} = \Theta_i z_{j,t-1}. \tag{8}$$

In equation (8), Θ_i represents the basic food requirements per capita for the reference good and z is the household's size. Hence farmers harvest their agricultural production and engage in market exchange if the production exceeds or falls behind the basic food requirements of the farmer's household. We assume a preference ordering in the consumption choice: first, farmers try to satisfy their cereals demand, then the vegetable needs and finally the demand for animal-based food. To compensate for a potential food deficit, expenditure will be subject to the following budget constraint:

$$\sum\nolimits_{i=1}^{3} \left[p_{i,t}\left(Y_{j,i,t} - c_{j,i,t}\right) \right] + w_t L_{j,t} + (1-\varsigma) M_{j,t-1} = M_{j,t}. \tag{9}$$

At the end of the period, the households become one period older, except for those who die, and the population size evolves according to the differential between the birth rate and the death rate.

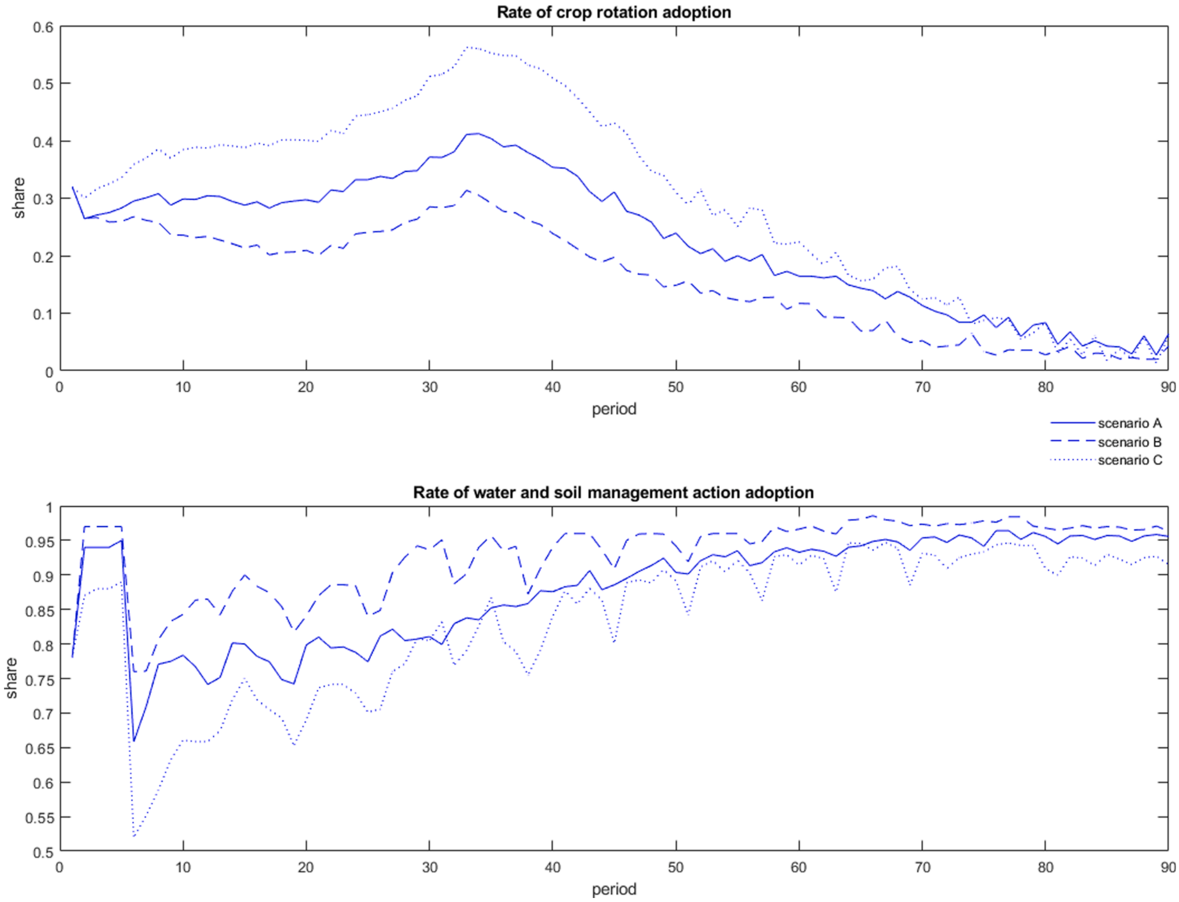

Fig. 6. CSA adoption rate in the three scenarios. This figure shows the average results from running 100 Monte Carlo simulations of the ABM in a village of 100 households over a 90 year period using scenario A (social network extension 60%), scenario B (social network extension 75%), and scenario C (social network extension 45%). The y-axis is the share of adopters in the farmers population. The solid line is the baseline scenario (A), the dashed line represents scenario B whereas the dotted line shows scenario C.

2.6. Aggregated variable dynamics

In this section we define the laws of motion for prices, wages, and population. In our baseline model, which follows the assumptions of Bakker et al. (2018) and Sankaranarayanan et al. (2020), we assume the existence of a village food market which is integrated enough so that local production does not endogenously change the commodity prices. Hence, the farmers are price takers and the agricultural commodity prices on the market evolve according to an exogenously given autoregressive process:

$$p_{i,t} = \varpi_{i,t} p_{i,t-1} + \varepsilon_{i,t}; \tag{10}$$

where $\varpi_{i,t}$ is an exogenous price evolution coefficient and $\varepsilon_{i,t}$ is a shock following a normal distribution.[3] For labour cost, we assume that the wage level in the economy is equal across farmers and evolves as follows:

$$w_t = \varpi_{w,t} w_{t-1} + \varepsilon_t; \tag{11}$$

In the baseline scenario, we assume that agents supply their labour to the other farmers within the village border to endogenously generate labour market dynamics and potential unemployment.

Finally, we assume that the prices of the agricultural production inputs ($p_{s,t}$) also evolve according to an exogenous autoregressive process, which is comparable to equation (10) in which farmers are price takers:

[3] In Section 3, we relax this assumption developing a scenario in which the constraints generated by geography and remoteness affect the price transmission endogenizing its evolution as follows: $\widehat{p}_{i,t} = \begin{cases} \beta p_{i,t} + \gamma\left[p_{i,t}(1+\varphi_{i,t})\right] where \varphi_{i,t} = f\left(\frac{\overline{C}_{i,t}}{Y_{i,t}}\right) if \overline{C}_{i,t} > Y_{i,t} \\ \beta p_{i,t} + \gamma\left[p_{i,t}(1-\varphi_{i,t})\right] where \varphi_{i,t} = f\left(\frac{Y_{i,t}}{\overline{C}_{i,t}}\right) if Y_{i,t} > \overline{C}_{i,t} \end{cases}$, Where $\varphi_{i,t}$ is increasing and $\varphi_{i,t}(1) = 0$. According to the new price definition, the food commodity price ($\widehat{p}_{i,t}$) in the interested area depends both by the exogenous price trend and by the actual production in the period in the area: if the production ($Y_{i,t}$) is higher than the local demand ($\overline{C}_{i,t}$), the households observe a reduction in the food commodities price, whereas if there is a shortage in the food commodity, its price increases.

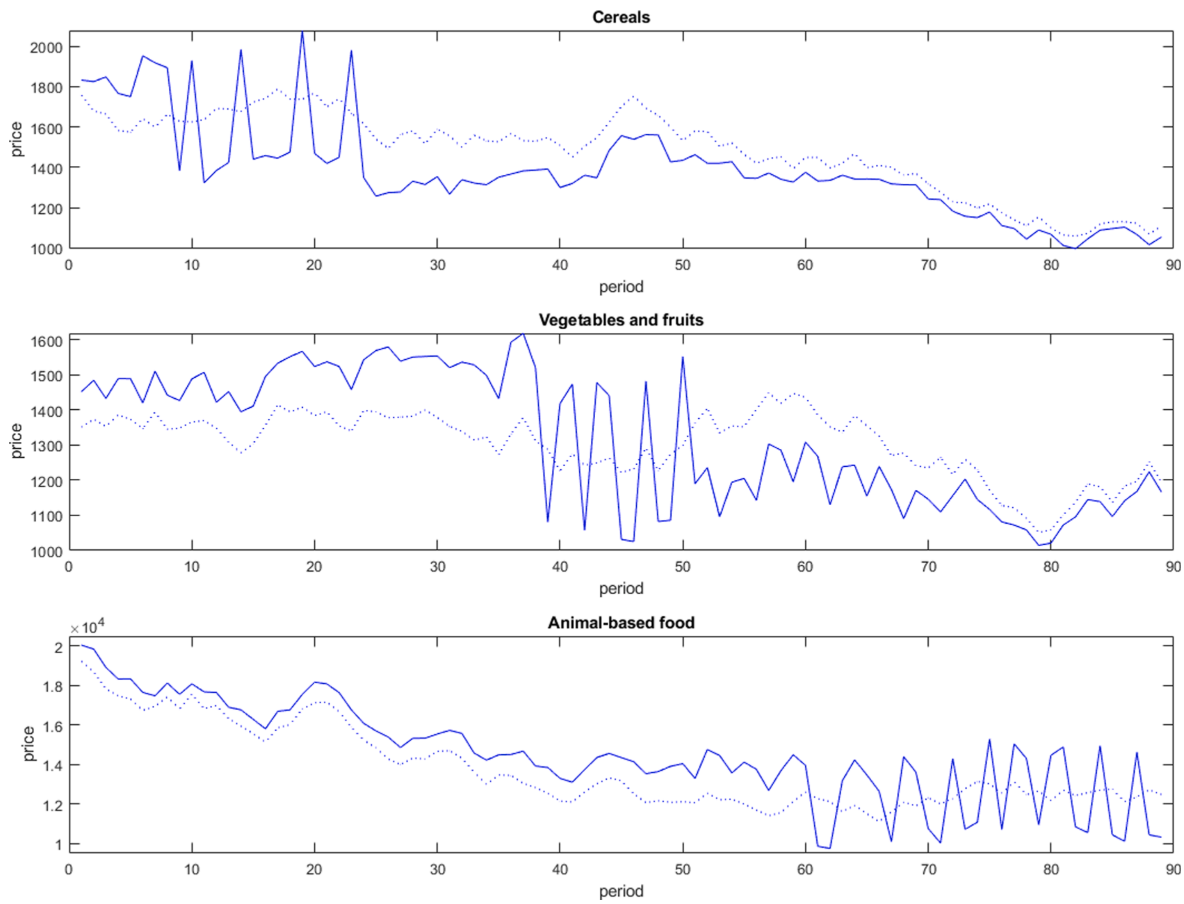

Fig. 7. Market price of food commodities. This figure shows the average results from running 100 Monte Carlo simulations of the ABM in a village of 100 households over a 90 year period using scenario A (exogenous price formation) and scenario D (endogenous price formation). The figures represent the price for cereals (first), vegetables and fruits (second), and animal-based food (third). The dotted line represents the price level if markets are integrated and prices are independent of local production and demand levels (Scenario A/Baseline), whereas the solid line is the price in non-integrated markets (Scenario D).

$$p_{s,t} = \varpi_{s,t} p_{s,t-1} + \varepsilon_{s,t}; \tag{12}$$

where $\varpi_{s,t}$ is an exogenous trend component and $\varepsilon_{s,t}$ is a shock following a normal distribution.

2.7. Scenarios and simulations

In the following sections, we run the ABM model to investigate whether CSA adoption dynamics positively affect the food security of the households. We design several representative scenarios (Table 1) to expand the analysis exploring: 1) how improving or reducing the extension services and community social network participation, which may change the information diffusion, affect the well-being of the farmers (Scenario A/Baseline, B, and C; Table 1); 2) how development policies (*e.g.,* road and railway construction) affecting price transmission can change adoption dynamics and food security (Scenario D); 3) whether the adoption of the CSA practices is an effective strategy to handle drastic climate change (Scenario E).

In all the scenarios we have defined a representative Ethiopian rural village composed of 100 small-holder subsistence farmers with, on average, one hectare cultivated land as is common in northwest Ethiopia.[4] Farmers participation in community social networks affect their CSA adoption rates. Following data collected by Simane et al. (2013) the community network involves 60% of the households under the reference Scenario A. We assume a growing population with a birth rate of 31.26 per 1000 people and a death rate of 6.67 per 1000 people (in line with Ethiopian data; United Nations, 2019). In line with the data for highland Ethiopia, the average initial family size is 5 people, but it evolves endogenously over time, affecting the total basic requirements and the households' well-being (see Table 2).

We assume a standardised African starch-based diet in line with the average value for Sub-Saharan Countries (FAO, 1997; 2008) as follows: 0.52 cereals, 0.27 vegetables and fruits, and 0.21 animal-based food products (diary and meat). In relation with these dietary needs, we define four indicators: food availability, food self-sufficiency, food instability, and food insecurity severity. Food availability is the ratio between actual food consumption and total food requirements, whereas self-sufficiency is defined as the ratio between self-production and total food requirement. Food instability is measured using the cereal import dependency ratio (FAO, 2011) which, in the case of a household, is the ratio of cereal net purchases over cereal consumption. The higher a household is dependent on cereal purchases, the lower the household's food stability is. Following Devereux (2006), we define severely food insecure households as those with food availability lower than 70%.

We model the effects of climate on agricultural production using a water stress measure calibrated to 14 climate models[5], which the

[4] For a wider description of the geographical location of the main data sources see Gebreyes et al. 2020 and Simane et al. (2013).

[5] The 14 selected climate models that perform best for the Ethiopian highlands are CanESM2, CESM1-BGC, CNRM-CM5, CSIRO-Mk3-6–0, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MPI-ESM-LR, MPI-ES-MR, MRI-CGCM3, and NorESM1-M.

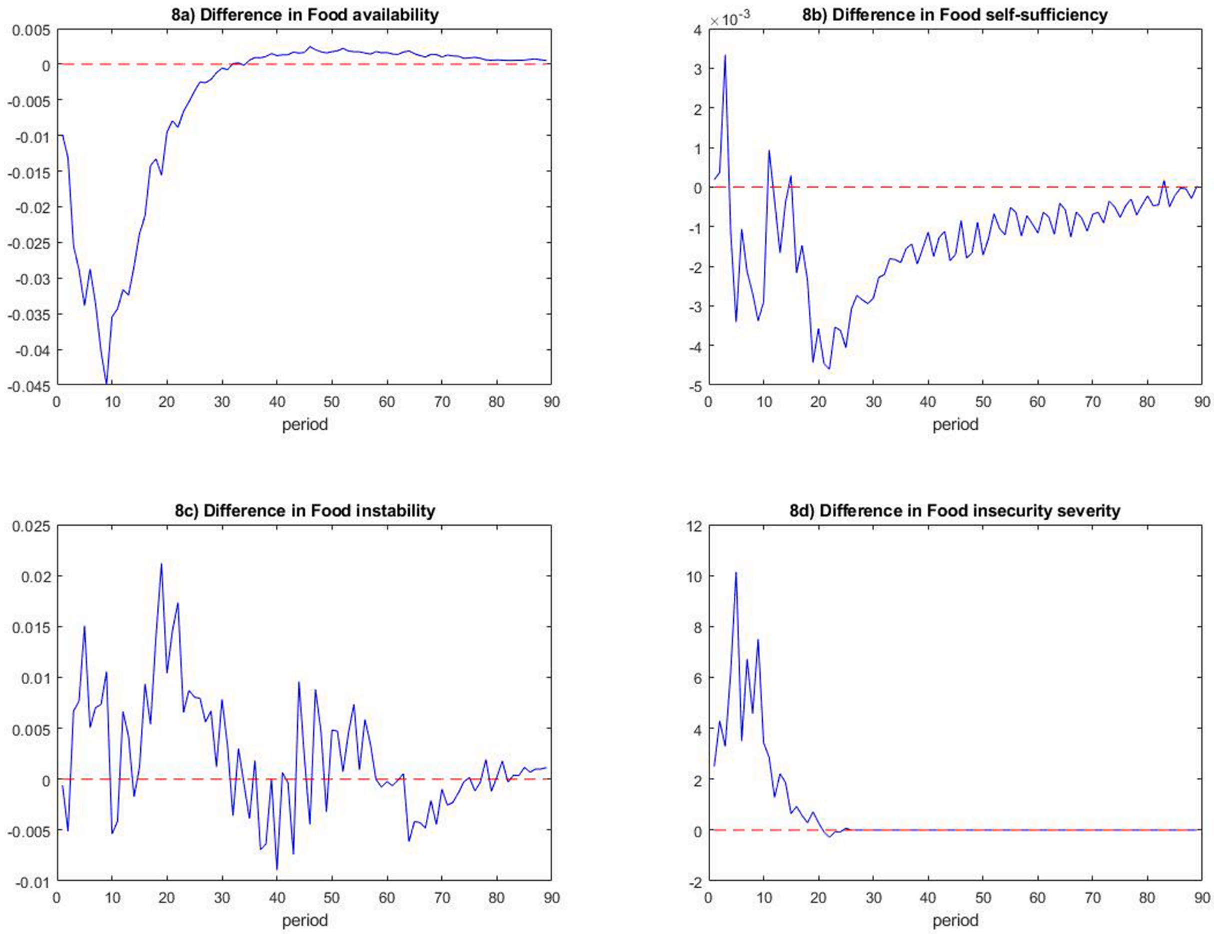

Fig. 8. Difference in food security levels in Scenario D compared to Scenario A. This figure represents the difference in the food security indicators in Scenario D compared to Scenario A (blue solid line), and the indifference level (red dashed line). For each scenario the average results from running 100 Monte Carlo simulations of the ABM in a village of 100 households over a 90-year period is computed, and the difference between the scenarios is calculated.

Table 3
Difference in CSA adaptation rates and food security indicators in Scenario E compared to Scenario A.

Scenario E minus Scenario A	first twenty years	last twenty years
Crop rotation adoption rate	−0.68%	+0.57%
WSA adoption rate	+2.01%	−2.08%
Food availability	−0.51%	+0.01%
Food self-sufficiency	−0.85%	+0.83%
Food instability	+0.78%	+1.41%
Food insecurity severity	+7.78%	−0.00%

This table shows the difference in the results from running 100 Monte Carlo simulations using scenario E (with 14 climate models under RCP 8.5) compared to Scenario A (with the same 14 climate models but under RCP 4.5).

literature finds perform the best for our study zone in Ethiopia (Eggen et al. 2019). In our case, we calculate the water stress parameter ρ based on daily data simulated by the 14 climate models with representative concentration pathways (RCP) 4.5 and 8.5 over 2006–2095 (90 periods). Data variables including daily minimum and maximum temperature, daily rainfall, and solar radiation are extracted from each of the 14 climate models in order to calculate the associated water stress parameter. The 14 climate models are selected from 20 models in the Coupled Model Intercomparison Project, Fifth generation (CMIP5; Taylor et al., 2012) and the data are obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP; Thrasher et al., 2012). In addition, the data are bias-corrected through comparing the model simulations to data observations in the contemporary climate regimes, including the application of Climate Hazard Group InfraRed Precipitation with Stations (CHIRPS) product (Funk et al., 2015) and the Global Data Assimilation System (GDAS) (Derber et al., 1991) over 1980–2009. As the rainfall amount during the main raining and growing season in the study region has been shown to be highly correlated with the phases of the El Niño–Southern Oscillation (ENSO) (*e.g.,* Gisilla et al., 2004; Zhang et al. 2016), the model selection criteria are based on whether the model is able to well represent ENSO and the rainfall characteristics over this climatic region (Eggen et al., 2019).

Simulations of the ABM were run with a Monte Carlo process repeated 100 times for a period of 90 years for each climate model. The Monte Carlo runs differ by the actual distribution/allocation of births, deaths, wealth, and CSA adopters among the households in each period.

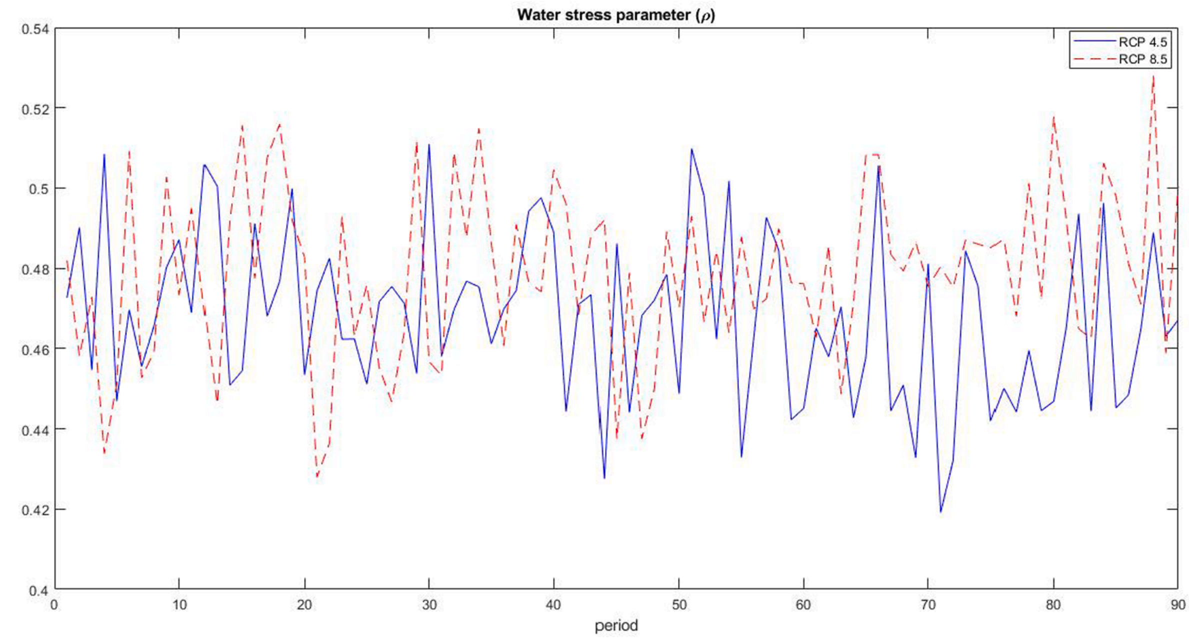

Fig. 9. Water stress parameter dynamics in the two scenarios. This figure shows the average water stress parameter among 14 climate models using RCP 4.5 (Scenario A) and RCP 8.5 (Scenario E).

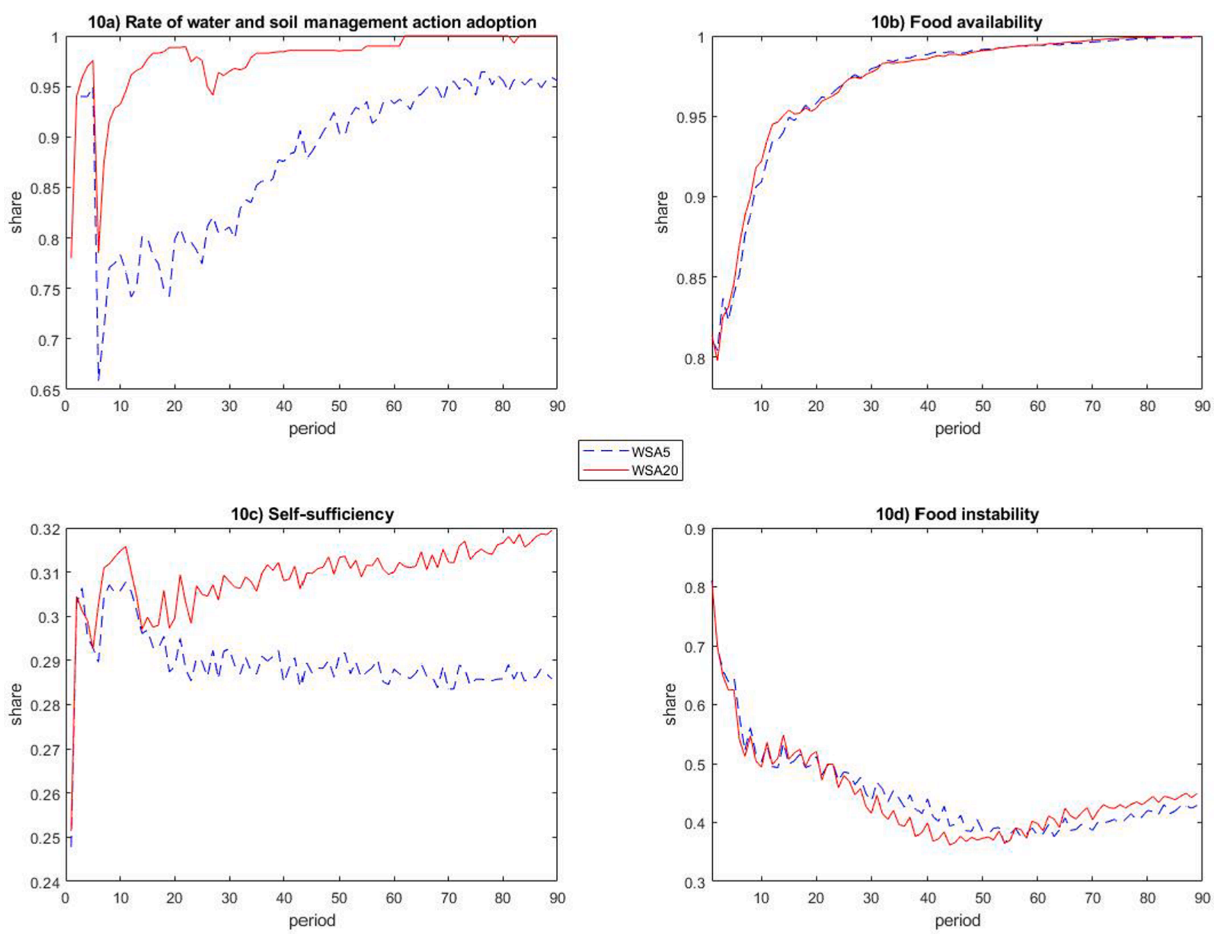

Fig. 10. WSA adoption and evolution of the food security dimensions. This figure shows the average results from running 100 Monte Carlo simulations for each of the 14 climate models under Baseline (Scenario A) (blue dashed line) vs. Baseline with longer lasting WSA practices (red solid line), i.e., 5 years vs. 20 years. Fig. 10a shows the average share of WSA adopters in the farmers population. Fig. 10b, c and d show the average level of the respective food security metrics - availability, self-sufficiency, and instability.

Table 4
Levels of food security dimensions in Baseline and Baseline with extended fertility range.

		Period 2	Period 30	Period 60	Period 90
Food availability – Baseline	10th	0.7897	0.9738	0.9929	0.9986
	mean	0.8110	0.9770	0.9940	0.9989
	90th	0.8273	0.9800	0.9950	0.9992
Food availability - Extended fertility range	10th	0.8018	0.9785	0.9947	0.9987
	mean	0.8026	0.9807	0.9955	0.9989
	90th	0.8032	0.9820	0.9960	0.9993
Self-sufficiency - Baseline	10th	0.0778	0.2306	0.2381	0.2284
	mean	0.2478	0.2921	0.2848	0.2858
	90th	0.4764	0.3333	0.3299	0.3273
Self-sufficiency - Extended fertility range	10th	0.0748	0.2719	0.2735	0.2411
	mean	0.2368	0.3085	0.2997	0.2902
	90th	0.4751	0.3333	0.3295	0.3273
Food instability - Baseline	10th	0.3911	0.1352	0.2018	0.3346
	mean	0.8115	0.4490	0.3909	0.4291
	90th	1	0.8350	0.4929	0.4891
Food instability - Extended fertility range	10th	0.4302	0.1290	0.2718	0.3641
	mean	0.8221	0.4252	0.4114	0.4374
	90th	1	0.8069	0.4812	0.4886
Food insecurity severity - Baseline	10th	27	0	0	0
	mean	29.8571	0	0	0
	90th	33.1000	0	0	0
Food insecurity severity - Extended fertility range	10th	26.9000	0	0	0
	mean	30.4286	0.0714	0	0
	90th	34.1000	0.1000	0	0

This table shows the results in different time periods from running 100 Monte Carlo simulations under Baseline (Scenario A) vs. Baseline with a wider soil fertility range.

The initial parameters on the farmer and household characteristics such as the average family size, average available land, CSA adoption rates as well as impact of ageing and network on CSA adoption are derived from the survey data described in Simane et al. (2013). The data also align closely with parameters in another published work that describes survey data from highland Ethiopia (Gebreyes et al., 2020). Table 2 shows the values of model parameters and the initial conditions for soil fertility and CSA adoption rates.[6] According to our parametrization, the initial soil fertility for each plot is distributed according to a uniform in the range [0.95; 1.05]. This low variance in the soil fertility is justified by the assumption that we are modelling a single village. In Section 3.5 we slightly relax these boundaries.

3. Results

The following subsections present the simulation results of food security and CSA adoption starting from the baseline scenario. Then, we investigate the role of community networks in the implementation of mitigation strategies showing the possible impact of farmer's wealth on food security dynamics. In Section 3.3 we change the food price transmission mechanism addressing the crucial role of market integration and actual food market access to the satisfaction of food basic needs. Finally, in scenario E the system is hit by a severe climate change shock aiming to explore the effectiveness of CSA adoption as a mitigation and adaptation strategy for severe climate change.[7]

3.1. *Individual decision and aggregated effects of climate smart agriculture adoption*

Looking at the ABM simulation results for aggregate dynamics of Scenario A (i.e., the baseline), Fig. 2 shows the climate smart agricultural adoption rate and the multidimensional aspects of food security: availability, self-sufficiency, instability, and food insecurity severity. The figures show 90% confidence bands as measures of model uncertainty. Fig. 2a and 2b show the adoption rates of CP and WSA techniques. Being costless, conservation practices exhibit a growing trend in their adoption in earlier periods, which reduces over time as the opportunity to share information on best practices among farmers increases. The community relationship explains, on the other hand, the growing trend in Fig. 2b because it positively affects the WSA adoption. Positive information on WSA generates a cascade effect through the physical water and soil management practices and their positive externalities on neighbours.

Fig. 2c represents the ratio between food consumption and total food requirements, highlighting the capability of farmers to reach household food security by self-production and by market exchanges. Fig. 2d represents the level of food security reached through self-production. The gap between food availability and self-sufficiency shows the crucial role played by market access in satisfying food basic needs. Indeed, in spite of the growing adoption of the soil and water management techniques (Fig. 2a), the food self-sufficiency level oscillates around 28.96% during the simulated period. Fig. 2e shows the dependence of household cereal consumption on cereals coming from the market, as a measure of instability. In the study area, the average percentage of purchased cereals over domestic supply of cereals is 44.89%. This index indicates the extent of vulnerability households are exposed to for cereal consumption, a main source of staples, when the access to market is disrupted or when the market price is volatile. Fig. 2f exhibits the number of households with severe food insecurity, i.e. households that are not able to reach a food availability level higher than 70%.

As shown by Fig. 3, starting from a situation where there is an almost equal land allocation among the three agricultural productions (cereals, vegetables and fruits, and pasture for animal-based food products), the ABM modeling shows that land allocated to cereals and pasture increases to a final level of around 80% of total land.[8] This redistribution of land among the crops favours the production of goods with higher economic returns (animal-based food) or that are more demanded by the households' starch-based diet (cereals). With higher earnings, the farmers try to satisfy the demand for other food commodities on the market. Allocating more land to the food commodity at the base of their diet, the farmers are able to reach higher levels of self-sufficiency. However, the growth in level of satisfaction through self-sufficiency is bounded by physical constraints of the agricultural sector with concave yields and by population growth.

Fig. 4 shows the results of the ABM simulations for food availability, i.e., the ratio between food consumption and total household food requirements. We divide the population in four groups according to climate smart agricultural practice adoption: non-adopters, farmers who adopt only WSA, adopters of CP but not WSA, and double adopters. Looking at the evolution of the food security indicators, all the four groups register an increasing trend in the average level of food availability, but farmers who adopt both CSA practices are able to reach the highest food security level. Comparing the dynamics of the four trends, it

[6] See Table A2 in the appendix for the references of the main parameters of the model. The parameters of the model are chosen to reflect data collected in rural Ethiopia and presented in Simane et al. (2013) and/or Gebreyes et al., (2020). They most closely resemble what is described as Agro-Ecosystem #3 in Simane et al. (2013), representing the rural villages in the area around Debra Markos, Ethiopia. The adoption rate parameters were provided by conversations with Dr. Belay Simane from estimates he conducted on the data collection exercise reported in Simane et al. (2013). These unpublished estimates from Simane were then further calibrated with those reported in Wossen et al. (2013).

[7] The following subsections display a set of results from simulations run in Matlab.

[8] See Fig. A1 in appendix for the percentile distribution of the land allocation among the simulation results.

is possible to see that CP adopters register a higher food availability level than WSA adopters in the first part of the simulated periods. This dominance can be mainly explained by the characteristic to be costless of the crop rotation adoption. Being costless, CP does not drain farmer economic resources which can be used on the food market to increase the household's food availability level. Additionally, CP has both a positive effect on food production and can benefit from the positive externality of the WSA adopters in the neighbourhood. Over time, the membership in the community network affects the farmer's beliefs on the benefits of WSA practices and therefore most of the farmers implement these practices (as shown in Fig. 2). This adoption produces positive externality from the beginning and increases the agricultural economic return also for WSA non adopter. Hence, having more available economic resources, farmers who were previously non adopters due to budget constraint can now implement WSA.[9] Moreover we find that water and soil practices have a more stable impact on food availability than crop rotation in general, and a stronger positive impact in the long-run.[10]

In summary, our analysis of the baseline scenario indicates that climate smart agriculture practice adoption is an effective strategy to improve the well-being of farmers faced by future climate change by increasing their food availability. Their food availability increases come through a combination of higher food production and market purchases given increases in income from selling agricultural production on the market. However, the positive number of severely food insecure farm households highlights how heterogeneity in wealth, in terms of economic resources and available land, plays a crucial role which may be lost looking only at the average effects.

3.2. The impact of social network in the climate smart adoption practices

This section uses the ABM to perform a comparative analysis on the role of social networks on farmers' ability to reach adequate food security for their household. The aim is to understand whether community social networks significantly increase the adaptive capacity of farmers through the sharing of best practices and mitigation strategies reducing their vulnerability in terms of food security. More precisely, we compare the system dynamics of the baseline scenario with two scenarios with altered social network participation rates. In Scenario B, the community network is wider with 75% of the farmers in the area participating in each period, whereas in Scenario C the share of participants reduces to 45%. These differences in community networks also allow us to see how CSA might perform in a zone with lower levels of social connectivity and cohesion.

Fig. 5 shows the results of the ABM simulations in Scenarios A, B and C on three dimensions of food security: availability, self-sufficiency, and instability. Each plot exhibits the distribution of a food security indicator level in the population for the three scenarios in one of the four demonstrated periods.[11]

Looking at food availability in Fig. 5, we see that initially ($t = 2$) the levels are comparable across scenarios. At $t = 30$, almost all households in Scenario A and B reach the highest categorical level of food availability, while in Scenario C, with smaller social networks among farmers, a few more households are left behind in the second to the highest food availability category. The lower social network participation reduces the possibility to share experiences among peers, negatively affecting the adoption of the water and soil management actions and reducing the number of farmers who give up crop rotation practices as shown in Fig. 6. Interestingly, it seems that for food availability an income effect emerges. Indeed, although both the CSA practices positively affect agricultural yields, only the adoption of WSA requires strong investments whereas CP does not need additional production costs leaving unaffected economic resources that the farmers can use to purchase food commodities on the market. A wider community network is beneficial if we look at the food security level achievable by self-production. Increasing the possibility to exchange information and learn best practices from neighbours, the adoption rate of WSA is higher (Fig. 6). This higher adoption rate strengthens the resilience of farmers to adverse and unexpected conditions, *e.g.,* reduced yield under climate impact and loss of market access due to physical constraints. Investing in these practices, the households are able to increase their yields positively affecting the food security achievable without market transaction and to reduce their dependence on cereals from other areas (i.e., higher food self-sufficiency and lower instability as shown in Fig. 5). This suggests the crucial role that social networks, market price dynamics of food commodities, and population wealth play in food security under future climate change.

3.3. The role of market access on food demand satisfaction

As shown in Section 3.2, market integration is important for food demand satisfaction when self-production is not able to achieve total household food demand. In this section we test the ABM with a scenario (Scenario D) where the transportation infrastructures are not as well developed, and the constraints generated by geography and remoteness affect price transmission. In this case the frictions in the food market endogenizes the evolution of prices, making them partially a function of local production and sales levels.

Reducing the market integration of the simulated village produces a growth in the price volatility of the food commodities, as shown in Fig. 7 (solid line). The price of vegetables and fruits, and animal-based food given limited market access are higher than the price when households do not have constraints on the market access (respectively + 1.36% and + 5.56% on average), whereas, thanks to its higher local supply, cereals have a lower average price (−6.12%). Apart from the average levels, it is worth noting that the prices of the commodities show higher volatility in less integrated markets, which decreases food availability and increases food instability and insecurity severity. Indeed, farmers living in remote areas or districts with less transportation infrastructure are more vulnerable to unexpected drops in yields because these directly affect the food available for supply and demand in the local market and the price of the food commodities on the market. The price dynamics can be explained by the complex relations between food preference, land use and low integration of the food market. Starting from a comparable distribution of land use among the food commodities in the two scenarios, the African starch diet based on cereals activates some feedback dynamics between land use and food price. In geographically remote villages (scenario D), given the cereal production, the high level of the demand for this food commodity pushes up its price (see footnote 11). Unsatisfied demand coupled with expectation for higher economic return from the cereals cultivation will induce farmers to allocate more land to cereals production in the next time period. Indeed, the land allocation is affected by the market driven mechanism. In the incoming period, in the village market there will be a higher supply of cereals that i) reduces the production deficit, ii) negatively affects the commodity price, iii) through the behavioural heuristic will produce a reduction in the expected economic return of cereals production for the following period leading to a shift in the land allocation among crops. The land allocation mechanism will spread the fluctuations originated in the cereals' variables (production, price, land used) to the other food commodities which in the meantime will become relatively more profitable

[9] The adoption of CSA practices is not complete, i.e. do not affect all the population, because new householders substituting died farmers can have negative beliefs on the CSA adoption benefits.

[10] For a separated representation of the food availability evolution for each farmer type see Fig. A2 in appendix with the average and percentile distribution of the simulation results.

[11] We do not represent food insecurity severity in Fig. 5 because it is graphically less readable. The share of farmers in severe food insecure conditions becomes close to zero in the second plot (from period 30) for all the scenarios, suggesting little meaningful differences across scenarios in this dimension.

reinforcing the oscillating feedback dynamics.

Fig. 8 shows the difference in food security levels reached by households in the ABM simulations between Scenario D and Scenario A/ Baseline. In Scenario A, where the area has high market integration (i.e., better connected with transport infrastructures), the farmers are more resilient to food shortages in their own district because we do not observe strong price oscillations which can reduce their ability to satisfy food demand by purchasing commodities on the market (see food availability; Fig. 8a). The higher average price levels farmers face in the market when purchasing food, the fewer economic resources remain to be invested in agricultural production. Even if the scenarios show comparable CSA adoption rates (the difference in adoption between scenarios D and A is less than 0.5%), the reduction in the economic endowment has a direct effect on agricultural productivity given that the farmers have more binding budget constraints for production input expenditures. This effect is even more severe for the farmers with less available resources, both in terms of land and economic assets, and it is translated into a wider share of population registering severe food insecurity in Scenario D than A, an absolute change of +27.14% (Fig. 8d).[12]

3.4. Can climate smart agriculture practices manage drastic climate change?

This section expands the analysis by comparing Scenario E with climate projections under RCP8.5 to Scenario A under RCP4.5. The aim of this analysis is to investigate whether, from a food security perspective, CSA practice adoption is an effective mitigation strategy to different pathways of climate projections.

As shown in Table 3, at the beginning of the simulations the farmers in Scenario E are worse off than in scenario A exhibiting a lower adoption rate of CP practices and a higher implementation of WSA techniques. However, the results are reversed in the last two decades of the time horizon. Over time, crop rotation adoption becomes higher in the Scenario E (+0.57%) whereas WSA adoption becomes lower (−2.08%). These inversions in the CSA implementation rates mean that farmers prefer sustaining the soil fertility adopting costless practices to improve the self-sufficiency (+0.83%), exploiting the positive effects of the WSA adoption (i.e. positive externalities in the neighbourhood) acting as a free-rider. This behaviour allows the farmer to spend the new savings from non-adopting WSA in the food market to reach a higher food availability level (+0.01%). The stronger role of food market access in this drastic climate change scenario is also represented by the deterioration in household food stability.

The reason why the results in the two scenarios are fairly similar despite major changes in the climate change scenario is shown in Fig. 9. Fig. 9 exhibits the average water stress parameter dynamics (ρ_t) among the 14 climate models in Scenario A and Scenario E.[13] Importantly, in the reference geographic area, the climate scenarios exhibit comparable water stress parameters in the first twenty periods, equal to 0.475 and 0.476 respectively for representative concentration pathway 8.5 and 4.5. However, in the last twenty periods, the representative concentration pathway 8.5 is coupled with a lower average water stress parameter (0.4857 in Scenario E and 0.4598 in Scenario A) positively affecting the crop yields and the food security metrics.

In the first twenty years, Scenario E leads to higher water stress on average and the variation of climate impacts on crops is also higher, and therefore farmers register a drastic reduction in the food self-sufficiency levels coupled with slightly lower food availability, compared to Scenario A. The increase in WSA adopters in the farmer population in Scenario E with respect to Scenario A indicates that WSA is chosen by the farmers as a better adaptation strategy to more severe climate impacts, although the strategy cannot fully counteract the adverse climate impact. In the last twenty years, crops in Scenario E are projected to endure less water stress than Scenario A, and therefore the food self-sufficiency in Scenario E is higher than Scenario A while food instability is higher indicating households rely on market purchases for cereal consumption more heavily in Scenario E than in Scenario A. Overall, the analysis suggests that farmers adopting CSA actions fare better than the non-adopters, in which the effect of water and soil management practices on households well-being is the strongest in the scenario with more severe climate impacts.[14]

3.5. Robustness check

In this section, we perform additional simulations by changing some key parameters in order to investigate the robustness of our results. First, we analyze the effect of the land fertility on the model results. In the previous analyses, we assume a low variance in the fertility among the plots (from 0.95 to 1.05). This parametrization can be justified by the assumption that we are modelling the CSA adoption and food dimension dynamics focusing on a single (and representative) village. Here we assume a stronger variance in soil fertility to test the model's sensitivity and adaptability. As shown in Fig. 10, we now extend the range of the initial soil fertility (from 0.9 to 1.10). It should be underlined that in these new simulations the variance of the soil fertility is wider but it has not changed the distribution. As shown by Table 4, extending the plot fertility range centered around the same mean does not strongly affect the average results. Hence, this model can be applied to study the impact of CSA practice adoption of food dimensions in other contexts adapting the fertility range, for example assuming that different locations or more extended areas (*e.g.* more villages) have a higher difference in soil fertility or a lower average level changing the parametrization (i.e. shifting the fertility window).

We investigate the robustness of the results with respect to the persistence of the WSA practices. In the following simulations we assume that the water control structures last for twenty periods without changing the fixed adoption cost ($\tau_{x,t}$).

Extending the duration of the WSA practices reduces the fixed cost per period of their implementation and therefore positively affects the adoption rate and the food security dimensions (see Fig. 10). For example, in the first half of the simulated periods, the scenario with WSA lasting for more periods registers an average increase in their adoptions by 14.04% than the baseline scenario with positive consequences especially on the food self-sufficiency. The reason can be explained by the fact that higher WSA adoption rate relaxes the water stress, increasing the crop yields. As a consequence, in the experiment with longer WSA persistence, the households will register higher food availability with lower food instability issues.

These simulations support the previous insights on the crucial role of the economic environment in CSA adoption and food needs satisfaction. Indeed, by extending the lasting periods of the WSA practices we are implicitly lessening the economic burden of their adoption increasing their appeal (or economic sustainability) for more farmers. In future research development we will extend the analysis introducing maintenance costs and depletion rate of the structures in line with Bazzana et al. (2020).

4. Policy implications

This work provides a proof of concept for how an ABM designed to represent a village in rural Africa can help understand the future dynamics

[12] See Fig. A3 in appendix for the percentile distribution of the food metrics of Scenario D.

[13] See Fig. A4 in appendix for the distribution of the water stress parameter in the two scenarios.

[14] See Fig. A5 in Appendix for the percentage difference in food availability level between the two scenarios in the first (last) twenty simulated periods.

of farmer adaptation to climate change through climate smart agriculture. In providing a forward looking model with endogenous interactions among agents, this modeling exercise, carefully calibrated to survey data from highland Ethiopia, develops new insights for policy makers beyond the micro-econometric work that has so far developed in the literature (Di Falco et al., 2011; Asfaw et al. 2012). Specifically it identifies multiple interlinked policy efforts that will be needed to maintain food security for Ethiopian households in the face of climate change.

The model results show the importance of farmer networks in CSA adoption, market infrastructure in maintaining farmer wealth and food security, the importance of the economic endowment of farmers especially in the case of costly long-term investments. Policy makers would do well to develop extension models for the roll out of CSA that take advantage of farmer networks for spreading information. Our model does, however, have a warning for policy makers, which is that where CSA techniques are not especially profitable in the short-term, these social networks can severely reduce adoption of a long-term potentially profitable technology. This suggests the potential need for policy makers to lessen the short-term economic burdens of climate adaptation through CSA adoption.

Policy makers also need to be aware that farmer willingness to adopt CSA does not guarantee food security for all farm households. Rather the model suggests that in zones with inadequate transport infrastructure we see volatility in endogenous local food prices that significantly reduces the ability of farmers to mitigate climate change through CSA adoption. This suggests that along with promoting climate smart agriculture, policy makers in Africa and elsewhere should seek to activate food markets and supply chains as a complementary climate adaptation policy.

Similarly, even when most farmers adopt CSA, our model also demonstrates significant heterogeneity in the food security benefits of CSA adoption. Up to a quarter of farmers, even with adaptation to climate change through CSA adoption, will still not reach adequate levels of food security for their households. Policy makers will need to develop additional policies to mitigate the effects of climate change to help this sector of the population.

Finally the modeling in this paper shows that climate adaptation through CSA adoption is useful but may not guarantee food security, especially with the strongest climate change scenarios. This suggests that policies to combat climate change are necessary complements to adaptation innovations. Policy makers cannot just hope that farmers can adapt their way out of climate change; they need to be focused on lessening the effects of climate change at the same time they are promoting adaptation.

5. Conclusions

We develop an Agent Based Model to investigate whether the Climate Smart Agriculture adoption dynamics positively affects food security of developing country farmers in a model calibrated to Ethiopian highland farmers. We do so using a multidimensional definition of the food security (availability, self-sufficiency, instability, and food insecurity severity) and incorporating social and ecological pressures (i.e., community networks, environmental externalities and climate change) to understand farmer adoption of short- and long-term CSA techniques in rural Ethiopia. The analysis shows that CSA adoption can be an effective strategy to improve the well-being of farmers through increases in crop yields and the economic returns from agricultural production (Gebreegziabher et al., 2016; Rasul and Sharma, 2016; Komarek et al., 2019). In coping with climate change, the model findings suggest that farmers adopting CSA fare better than non-adopters (Michler et al., 2019), although CSA practice adoption is not able to fully counterbalance the severe climate pressures. These results are in line with the empirical findings in other Sub-Saharan locations and confirm in a longer-term dynamic way the static results currently found in the literature (Mango et al., 2017). A high cost investment strategy such as WSA, however, is not always suitable for farmers who aim to reach higher food availability in a relatively short time frame. As shown also by the empirical work of Di Falco et al. (2011), the food security response to adaptation strategies critically depends on farmers' investment capacity and economic resources for market purchases to satisfy consumption needs especially in the short-term.

Among the novel findings is that by investigating the dynamic role of social networks, the analysis demonstrates the importance of community relationships to exchange information and best practices to increase the adoption rate of climate smart agriculture techniques (Makate et al., 2019). Also by modeling the local community within which the farmers live, our simulations demonstrate that the economic environment plays an equally crucial role in the success of CSA adoption, because both market price dynamics of food commodities and population wealth play important roles in food security even with farmer adaptation of climate smart agriculture. Farmers living in more remote areas become more vulnerable to food shortage in their own district with CSA adoption. Having worse connections to food markets, these farmers face stronger price oscillations which negatively affect their food stability and well-being. This outcome is even more severe for the poorer farmers, both in terms of available land and economic assets.

Methodologically this work adds to the literature on climate adaptation by demonstrating how agent-based model simulations that take into account neighbourhood learning dynamics and market conditions can provide additional understanding to how farmers might adapt to climate change in the future. The farmers in this model are not passive recipients of climate change, but active learners who learn from their neighbours, past experiences, past climate, and market opportunities. The work shows how to move beyond backward looking models of climate smart agriculture to estimating adaptation possibilities in complex socio-economic environments such as the African context. Having demonstrated how an agent-based model can simulate farmer adaptation with climate smart agriculture, we see many future research avenues for use of this and similar agent-based models. These include calibrating the model to other locations in Africa and beyond, analysing other CSA-type interventions, and testing how market and supply chain interventions might inform policy makers about the ability of households to adapt to future climate change.

CRediT authorship contribution statement

Davide Bazzana: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Jeremy Foltz:** Conceptualization, Writing – original draft, Writing – review & editing. **Ying Zhang:** Writing – review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Appendix A

In Table A1 we show the sources for the parameters to calibrate our model. The parameters of the model are chosen to reflect the actual data presented in Simane et al. (2013) and Gebreyes et al., (2020), which report on survey data from rural areas of central Ethiopia. They most closely represent what is described as Agro-Ecosystem #3 in Simane et al. (2013), which describes rural villages in the area around Debra Markos, Ethiopia. The adoption rate parameters were provided by Dr. Belay Simane from estimates he calculated in the same data collection exercise reported in Simane et al. (2013). Those estimates were revised to be consistent with the social network estimates in Wossen et al. (2013). Broadly the data also comports with other data we can find in the literature about Ethiopian rural

Table A1
Sources of the main parameters of the model.

Parameter	Value	Source
Maximum number of plots per household	20	Headley et al., 2014; Gebreyes et al. 2020
Discount factor	0.9	Duflo et al. 2011
Share of land affected by market driven mechanisms (i.e. cash crops)	0.25	Gebreyes et al. 2020; Bazzana et al. 2021
Share of income re-invested in the production process	0.95	World Bank (2013)
Bias coefficient	1	Gebreyes et al. 2020; Bazzana et al. 2021
Average family size	5	Headley et al., 2014; Gebreyes et al. 2020
Impact of age on WSA adoption propensity	0	Simane et al. 2013; Wossen et al., 2013
Impact of age on CP adoption propensity	−0.012	Simane et al. 2013; Wossen et al., 2013
Network impact on WSA adoption propensity	+0.65	Simane et al. 2013
Network impact on CP adoption propensity	−0.45	Simane et al. 2013
Participation in social networks	60%	Di Falco et al., 2011; Simane et al. 2013
Percentage of farms with irrigation	30%	Simane et al. 2013; Gebreyes et al. 2020
Initial WSA adoption rate	78%	Simane et al. 2013
Initial CP adoption rate	32%	Asfaw et al., 2012; Simane et al. 2013
Population birth rate	31.26‰	United Nations, 2019
Population death rate	6.67‰	United Nations, 2019

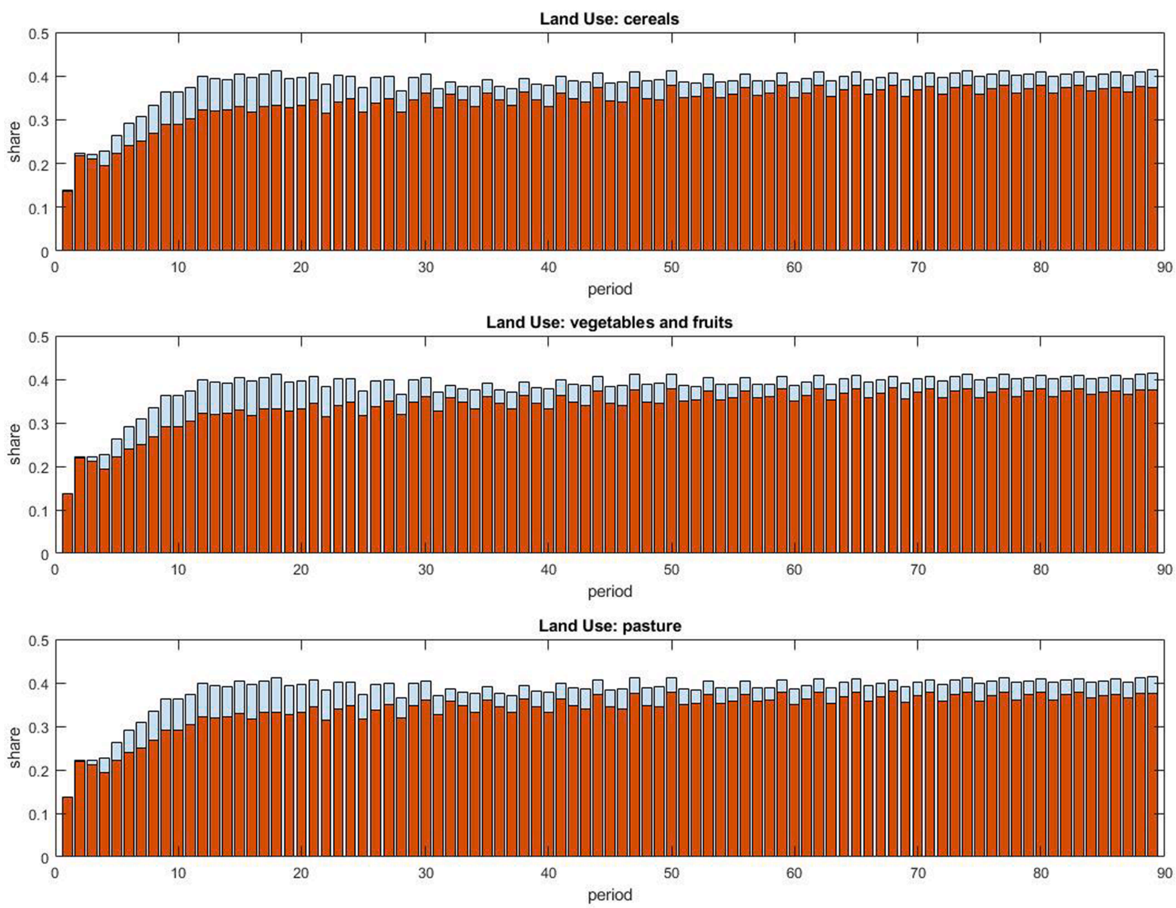

Fig. A1. Average land allocation among agricultural productions (percentiles). The figure shows the results range from running 100 Monte Carlo simulations of the ABM using scenario A for the 14 climate models. The y-axis is the share of total available land allocated to each crop. Red bars represent the 10th percentile whereas the light blue bars are the 90th percentile.

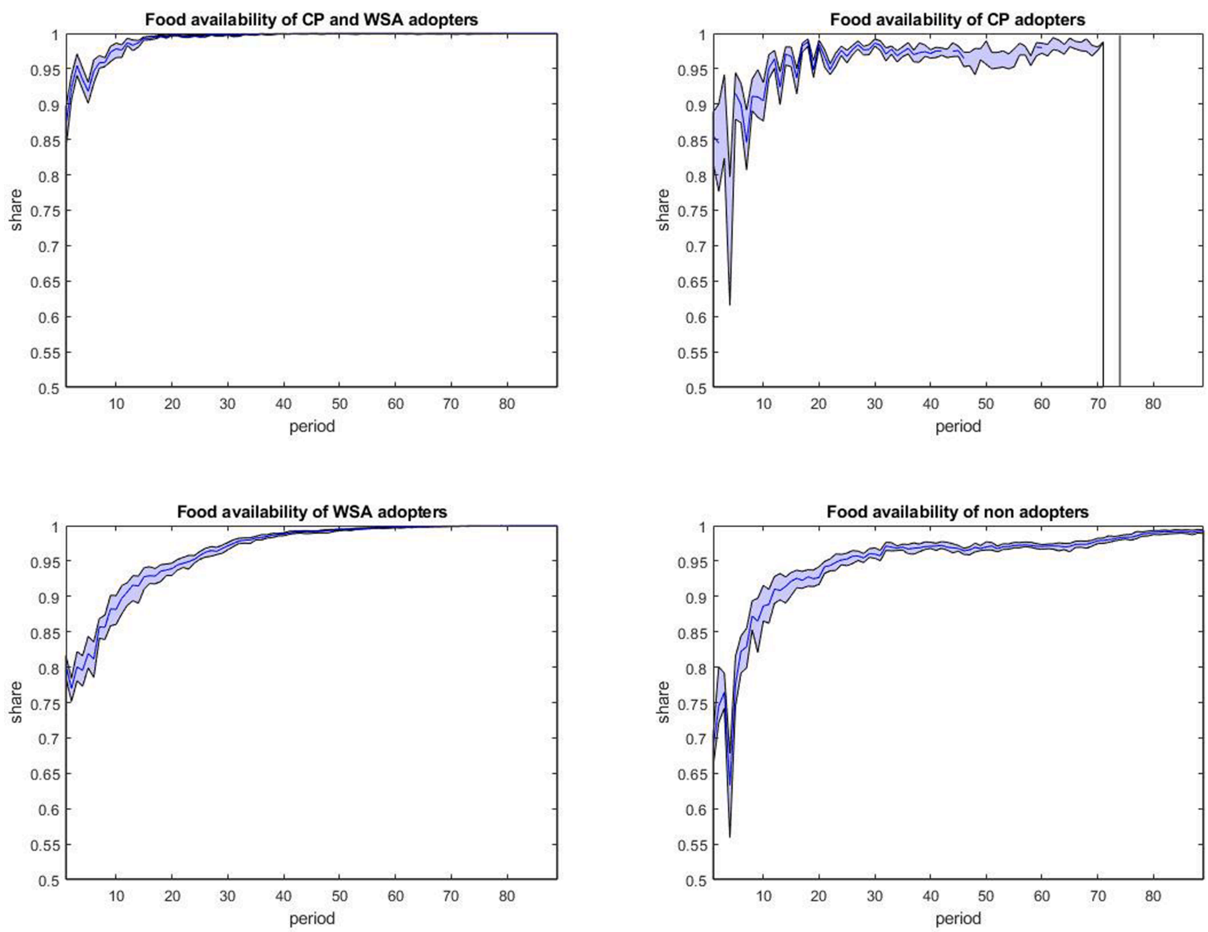

Fig. A2. Food availability evolution by CSA adoption (percentiles). The figure shows the results range from running 100 Monte Carlo simulations of the ABM using scenario A for the 14 climate models. The y-axis is the level of food availability for the four types of farmers: double adopters, WSA adopters (solid line), CP adopters, non adopters. The continuous line represents the average results whereas the half-transparent band shows the results between the 10th and the 90th percentile.

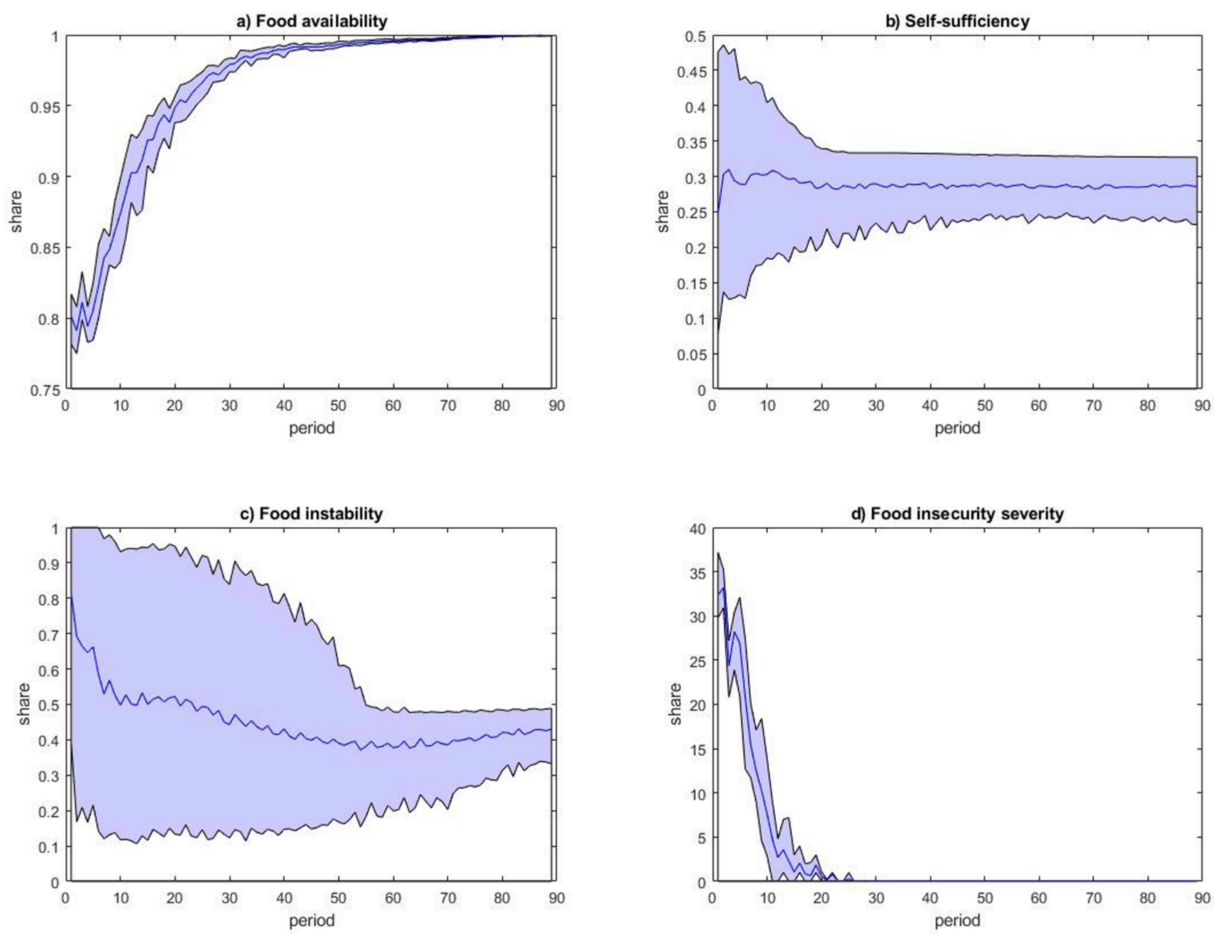

Fig. A3. Evolution of the food security dimensions in Scenario D. This figure shows the results from running 100 Monte Carlo simulations of the ABM for each climate scenario. Figure a, b and c show the level of the respective food security metric - availability, self-sufficiency, and instability, whereas Figure d shows the average number of households (share in the population) as defined in food insecurity severity. The blue line represents the average level whereas the half-transparent band shows the results between the 10th and the 90th percentile.

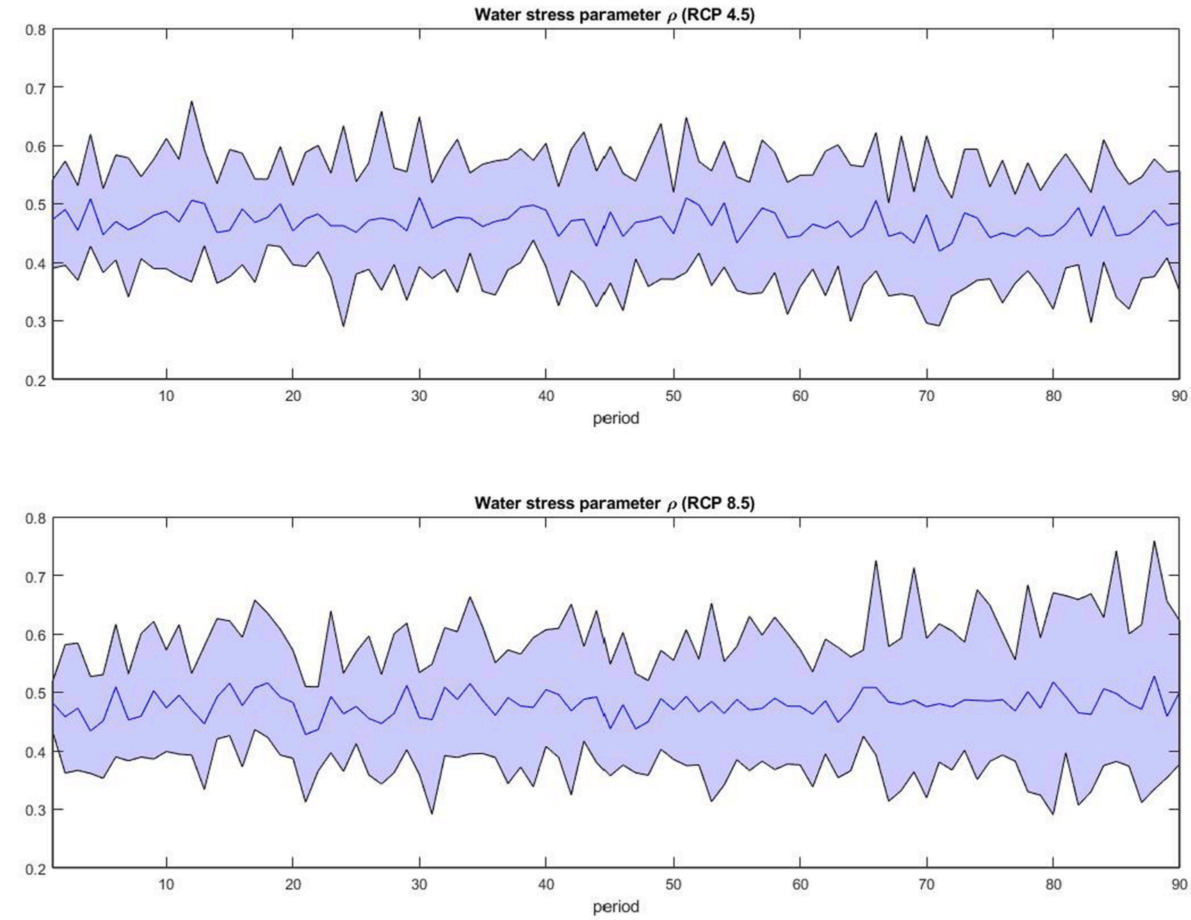

Fig. A4. Water stress parameter dynamics in the two scenarios, This figure shows the average, the 10th and 90th percentile of the water stress parameter among 14 climate models using RCP 4.5 (Scenario A) and RCP 8.5 (Scenario E).

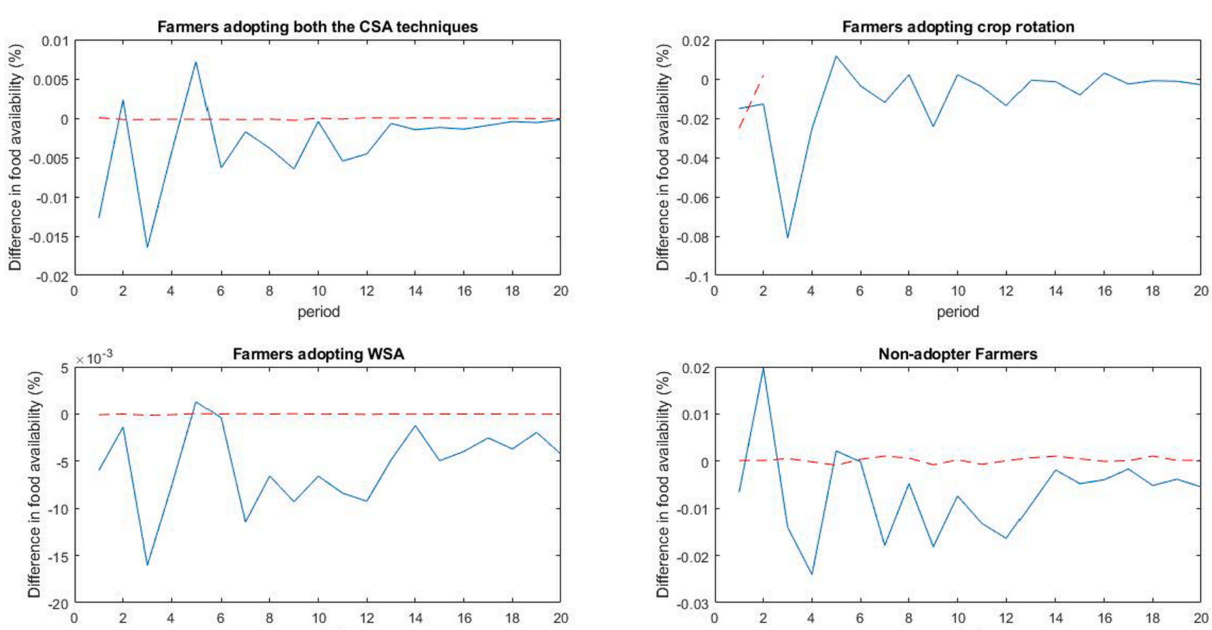

Fig. A5. Difference in Food availability according to the farmer type in Scenario E compared to Scenario A. This figure presents the percentage difference in the food availability in Scenario E compared to Scenario A for the four adopter types. For each scenario the average results from running 100 Monte Carlo simulations are computed, and the difference between the scenarios is calculated. The solid line represents the difference in the first twenty periods, whereas the dashed line represents the percentage difference in the last twenty periods.

areas, such as Asfaw et al. (2012); Di Falco et al. (2011); and Headley et al. (2014). Additional information to appropriately calibrate the model to a rural Ethiopian setting comes from World Bank (2013) and the United Nations (2019) (see Figs A1–A5).

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