Agricultural Systems 190 (2021) 103131

Contents lists available at ScienceDirect

Agricultural Systems

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

Better before worse trajectories in food systems? An investigation of synergies and trade-offs through climate-smart agriculture and system dynamics

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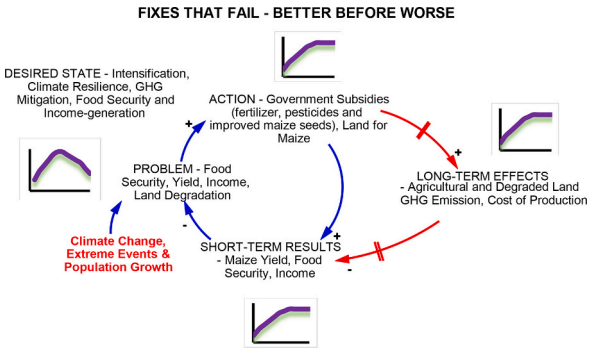
HIGHLIGHTS

- Synergies and trade-offs emerge over time due to the complex adaptive nature of food systems.
- Focus on intensification leads to a "better before worse" pattern; post 2035 trade-offs emerge, positive trends reverse.
- The food system structure and purpose should change to mitigate climatic and other risks.
- The application of system tools and climate-smart agriculture can transform food systems.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Jagadish Timsina

Keywords:
Climate change
Food security
Smallholder agriculture
Systems thinking
System dynamics modelling
West Africa

ABSTRACT

CONTEXT: Food systems face multiple challenges simultaneously: provision to a growing population, adaptation to more extreme and frequent climate change risks, and reduction of their considerable greenhouse gas (GHG) emissions. Food system interventions and policies give rise to synergies and trade-offs that emerge over time due to the dynamic nature and interconnections of system elements. Analysis of an entire food system is necessary to identify synergies that bring simultaneous benefits and mitigate trade-offs, both short- and long-term.
OBJECTIVE: Our study aims to inform the sustainable transformation of food systems by identifying short- and long-term synergies and trade-offs in the climate-smart village (CSV) Lawra-Jirapa in northern Ghana under the current practices, technologies, policies, and trends of population growth, extreme events, and climate change impacts.

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https://doi.org/10.1016/j.agsy.2021.103131
Received 5 August 2020; Received in revised form 9 March 2021; Accepted 12 March 2021
Available online 19 April 2021

METHODS: We develop a system dynamics model to simulate the food system in the CSV between 2011 and 2060. We apply the climate-smart agriculture (CSA) approach as a diagnostic tool to the CSV system to reveal the short- and long-term trade-offs and synergies between the CSA goals.
RESULTS AND CONCLUSIONS: The simulation results reveal short-term progress towards the goal of increased productivity and income, with trade-offs in the goals of GHG removal, climate adaptation, and resilience. In the long term, post-2035, current agriculture practices, technologies, and policies inside and outside the CSV boundaries result in trade-offs across all three CSA goals, and progress made towards these goals is reversed. The CSV system behaviour, thus, exhibits a "better before worse" pattern.
SIGNIFICANCE: The analysis demonstrates an approach, which considers simultaneously all three CSA goals, to identify synergies and mitigate trade-offs in an entire food system. The findings suggest that understanding the dynamics of food systems is a precursor to their sustainable transformation. This transformation will entail changes to the food system's goals and structure with equal attention to short- and long-term outcomes.

1. Introduction

The Food and Agriculture Organisation estimates that by 2050, our food systems will have to produce 50% more food to feed a rapidly growing population (FAO, 2017a, 2017b). This increase in food production will present socio-economic challenges and increase greenhouse gas (GHG) emissions and land-use changes with an impact on the natural environment and biodiversity (Mbow et al., 2019; Herrero and Aziz, 2019). There is an urgent need to minimize the yield gap and the environmental stresses induced by increased agricultural production, and simultaneously adapt and build agricultural system resilience to climate change risks (Pradhan et al., 2015).

In light of these multiple challenges to sustainable food security and ecosystem health, integrated approaches are sought to enable and facilitate synergies between low-carbon and climate-resilient pathways (Mbow et al., 2019). Climate-smart agriculture (CSA) is such an integrated approach that introduces context-specific technologies and practices into food systems. CSA aims to meet the triple goals of sustainable agricultural intensification, climate change (CC) adaptation, and GHG mitigation to support food security under CC's new realities (Lipper et al., 2018). However, the interconnections and dynamics between food system elements give rise to synergies and trade-offs that emerge over time within and between the CSA goals (Steenwerth et al., 2014; Aggarwal et al., 2018). Synergies emerge when a desirable change in one goal also contributes directly or indirectly towards other goals. Trade-offs emerge when efforts to reach one goal undermine or limit the potential of reaching another goal in the short- or long-term (Pradhan et al., 2017; Fader et al., 2018).

While CSA aims to meet the triple goals simultaneously, their order and priority vary in practice and often depend on the local context (Totin et al., 2018). Consequently, considerable attention should be given to goal priority in CSA application, the implementation of practices in a given context, and their short- and long-term impacts (Partey et al., 2018). For instance, in developing African countries, food insecurity is prevalent, vulnerability and exposure to climate change risks are high, and agriculture's contribution to GHG emissions increase rapidly (Tongwane and Moeletsi, 2018). In this context, sustainable intensification and adaptation goals are the priority, and CSA interventions should involve mitigating the trade-offs between the triple goals and weighing the costs and benefits of different options (Lipper et al., 2018; Thornton et al., 2018).

However, prioritizing some goals over others raises the question as to whether interventions could truly be considered climate-smart (Neufeldt et al., 2013; Hochman et al., 2017; Thornton et al., 2018). This is because a CSA that focuses more on some goals often lacks evidence on the trade-offs and synergies between the triple goals (Saj et al., 2017). The lack of evidence limits opportunities to learn and mitigate trade-offs and may lead to maladaptation and establishment of unsustainable food system practices in the short- or long-term (Aggarwal et al., 2018; Martinez-Baron et al., 2018). Thus, it is necessary to persistently consider the triple goals equally in CSA-related research and development projects (Saj et al., 2017). The synergies and trade-offs between the triple goals of CSA are especially important in light of the need for sustainable transformation of our food systems (FAO, 2019).

The CSA approach can be applied to the increasing number of climate-smart villages (CSV) established worldwide to understand their system-wide impact and inform the scaling-up of sustainable food systems. To do so, it is necessary to identify and understand the interdependencies of context-specific socio-economic and environmental elements of food systems and their dynamics (Steenwerth et al., 2014; Aggarwal et al., 2018). This task requires the use of systems tools and approaches because sector-specific approaches that focus on a specific part of the food system ignore its multidisciplinary nature, while linear approaches fail to capture the complexity and the range of interactions and dynamic feedback loops within food systems (Monasterolo and Mollona, 2015; Monasterolo et al., 2016). Analysis of a food system can identify and address synergies and trade-offs and result in integrated adaptation and mitigation interventions (Rosenzweig et al., 2020). Moreover, it can contribute towards the UN Sustainable Development Goals (SDG) of zero hunger (SDG2), poverty elimination (SDG1), gender equality (SDG5), climate action (SDG13), and life on land (SDG15) (FAO, 2019) and move the global system into the safe and just operating space (Pradhan et al., 2017).

An interdisciplinary simulation approach is necessary to understand food system dynamics over time and inform the scaling-up of sustainable food systems through the CSA approach (Jagustović et al., 2019). The use of system dynamics (SD) to investigate the impact of CSA interventions was proposed (Muetzelfeldt, 2010), yet there is no follow up work in this direction. To fill this gap, we develop a system dynamics model to simulate short- and long-term dynamics in the climate-smart village (CSV) site in northern Ghana, under the current practices, technologies, policies, and trends of population growth, extreme events, and climate change impacts. We demonstrate that the CSA approach as a diagnostic tool can be combined effectively with the SD method to capture, explore, and simulate the complex feedback relationships between the food system elements in the Lawra-Jirapa CSV site. Simulation results reveal the short-term and long-term trade-offs and synergies within and between the CSA goals at the household and landscape levels.

2. Materials and methods

2.1. The system dynamics methodology

We conduct an exploratory, interdisciplinary study and apply SD to investigate and analyse a complex food system and explore the outcomes of current policies and practices. SD is a computer-based simulation method used to model, simulate, and analyse dynamic complex systems. SD and agent-based modelling are used widely in sustainability transition research (Papachristos, 2011; Holtz et al., 2015; Papachristos and Adamides, 2016; Köhler et al., 2018; Kotir et al., 2016; Papachristos, 2014, 2018, 2019; Papachristos and Struben, 2019; Karlsen et al., 2019).

Grounded in the theory of information feedback control and systems thinking (Forrester, 1961), the approach was developed to characterize complex, non-linear systems by capturing causal relationships, feedback loops, and delays between system components (Sterman, 2000; Langsdale et al., 2009). SD starts from the premise that system structure drives its behaviour (Richardson, 2011; Bala et al., 2017; Elsawah et al., 2017).

Our SD model development includes qualitative and quantitative modelling stages, and they are seen as interdependent and complementary to aid system-wide analysis of key processes in the food system at the Lawra-Jirapa CSV site. The model development process draws on lessons and SD best practices (Rahmandad and Sterman, 2012; Elsawah et al., 2017). The iterative modelling process implemented in this paper has four steps: (i) identification of system drivers and processes, (ii) qualitative modelling of the causal processes operating in the system, leading to a basic model structure, (iii) development of stock-and-flow diagrams (SFD) and a simulation model, and (iv) model validation and simulation to analyse the dynamics of the entire food system. Data on the conditions in the Lawra-Jirapa CSV site supported the conceptualization, operationalisation, and validation of the SD model. We provide an overview of the modelling context in section 2.2, and we demonstrate the implementation of each modelling step in section 2.3.

2.2. Modelling context: Lawra-Jirapa climate-smart village

The Lawra-Jirapa CSV of the case study is a cluster of seven villages situated in the Upper West Region (UWR) of northern Ghana in the Guinea Savana agro-ecological zone. The CSV site was established in 2011 as part of the CGIAR global research programme on Climate Change, Agriculture and Food Security (CCAFS), and in collaboration with local communities, practitioners, and scientists. CSVs are research and development sites used to design CSA models and to investigate and document lessons for policymakers, agricultural development practitioners, and investors (Westermann et al., 2015; Aggarwal et al., 2018). The aim is to conduct transformative agricultural investigation considering socio-economic dynamics, climate variability, and climate change.

The UWR has a unimodal rainy season from May to September and seven to eight months of dry season with a mean annual rainfall of 1035 mm (Lacombe and McCartney, 2012). The CSV site is characterized by temporal climate variability and dry spells during the rainy season lasting between three days and four weeks (Kranjac-Berisavljevic et al., 2014). Analyses of historical climate data on rainfall and temperature for the last (24–36 years) is consistent with the perception of climate variability among smallholders in the CSV site (Ndamani and Watanabe, 2016; Nyantakyi-Frimpong and Kerr, 2015; Dakurah, 2018). Both note a shift in planting season from mid-February and mid-March to mid-April and mid-May (Lacombe and McCartney, 2012) and a decreasing rainfall trend from 1980 to 2015 (Asare-Nuamah and Botchway, 2019). The mean annual temperature (from 1982 to 2012) was 33.7 °C, an increase of 1.0 °C since 1960 (McSweeney et al., 2008). The CCAFS research programme documented the socio-economic and environmental conditions in the site, and identified technologies and practices guided by the CSA approach and informed by climate change projections. The midline survey in 2017 assessed changes since 2011 and whether they helped villages adapt to and mitigate climate change (Ouedraogo et al., 2019).

The midline survey reports an increase in household size and demand for land and a decrease in technology adoption related to soil fertility and tree/agroforestry. The number of households that adopt tree management and soil management practices reduced, with 30% fewer households involved in tree management and 15% fewer in soil management. The midline survey reported continuous pressure on the tree population in the absence of alternative sources of income and energy, showing no changes in fuel demand for domestic and commercial use. In 2017, the population continued to perceive deforestation, soil degradation/erosion, population growth, and rainfall changes as the main drivers of change.

The agricultural product diversity index declined, and only 14% of households were producing 9 or more products (high diversity) by 2017, compared to 46% in 2011, while 31.4% of households were producing 1–4 products (low diversity) by 2017, compared to 1% in 2011. Other studies confirmed maize dominance in the farming system with more land for growing maize than other crops (Nyantakyi-Frimpong and Kerr, 2015). This is because maize has replaced sorghum and millet, and it is the preferred cereal grown for household consumption, with over 80% of respondents in the CSV site consuming maize for breakfast, lunch, and dinner (Dakurah, 2018).

The CCAFS midline survey recorded an increase in the use of inputs, including pesticides, fertilizer, and improved maize seeds, with 81% of households reporting use of inputs in 2017, compared to 31% of households in 2011. This was expected, as the UWR is the major target region of Ghana's Fertilizer Subsidy Program (GFSP). Access to inputs is growing due to an increase in the subsidy rate from 12.5% to 50% in 2017, and a more flexible payment plan (Nimako, 2019). At the same time, access to subsidies for maize production has also reduced the variety of food production and consumption at the household level (Kermah, 2020).

Despite the increased use of inputs, both baseline and midline CCAFS surveys report low agricultural productivity and frequent crop failures due to poor soil quality and unreliable rainfall. A 2018 survey in the CSV site recorded a maize yield of up to 573 kg/ha using minimal inputs that doubled with intense fertilizer use provided through subsidies (Nimako, 2019). Bua et al. (2020) confirm that the range of maize yield in the UWR is 0–500 kg/ha, and yield response to recommended fertilizer will increase between 500 and 1200 kg/ha from the current yield level. Maize yield losses occur frequently in UWR due to extreme events (i.e., drought, dry spells, floods, and pests) (Ndamani and Watanabe, 2016). For example, the appearance and infestation of fall armyworm in 2017–2018 resulted in 17–21% yield loss (Koffi et al., 2020). The vulnerability of maize yield to drought is high because of low adaptive capacity and rain-fed agriculture (Antwi-Agyei et al., 2012), with a significant impact on food security (Kermah, 2020).

The CCAFS midline survey furthermore reports a minimal improvement in food security, with 46.2% households being food insecure for 3–4 months in 2017 as compared to 42% in 2011, and 33.3% of households being food insecure 5–6 months in 2017 as compared to 38% in 2011. Other studies report that only 37% of households in the UWR could survive on their food production for six months of the year

Table 1
Key variables of interest.

FAO indicators for monitoring and evaluating CSA	Variable in the Lawra-Jirapa CSV model	Unit
Sustainably increasing agricultural productivity and incomes		
Yield per hectare	Maize yield per hectare	kg/ha
Income	Maize gross profit per household	GHC/hh
Percentage of the population that is food insecure	Months of household food availability	Month/hh
Agricultural production	Maize production in Lawra-Jirapa CSV	kg
Changes in biophysical characteristics	Biomass availability	t/ha
Changes in land-use area	Land for maize, land for other crops, abandoned land, arable land	ha
Adapting and building resilience to climate change		
Number of soil and water conservation works	Number of households adopting CSA	No of hh
Area of farmland under CSA technologies	Hectares of land under CSA practices	ha/year
Removing GHG emissions		
Reduced GHG emissions	Estimated GHG balance	tCO_2e/ha/year
Number of soil and water conservation works	Number of households mitigating	No of hh
Changes in land-use area	Land for maize, land for other crops, abandoned land, arable land	ha

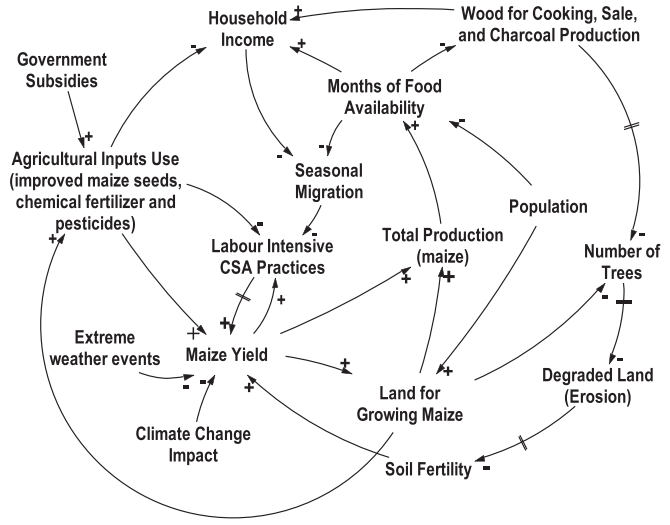

Fig. 1. The final CLD representing the merged mental models of CSV female and male farmers and CCAFS scientists. The arrows show the causality, and plus/minus signs at the arrowhead show the polarity of the relationships between variables. For example, when the variable *"agricultural inputs use"* increases (decreases), *"household income"* decreases (increases). This is indicated with a (−) sign at the arrowhead. Similarly, when *"household income"* increases (decreases), *"seasonal migration"* decreases (increases). Conversely, when *"months of food availability"* increases (decreases), then *"household income"* increases (decreases). Double lines (//) on the arrow lines indicate a time delay in response to the stimuli.

(Kermah, 2020) and that 60% of households in Jirapa and 55% in Lawra face severe food insecurity (Atuoye et al., 2017).

With regard to climate change projections, the mean annual temperature in Ghana is expected to increase by 1.0° to 3.0 °C by the 2060s, with widespread drought and warming most rapid in the north of Ghana (McSweeney et al., 2008; Masih et al., 2014; Klutse et al., 2020). Models project an increase in daily rainfall intensity (Weber et al., 2018), a delay in the onset of rainfall, and a reduction in the rainy season's overall length. Maize yield losses are projected at 22% by mid-century; however, the aggregate results hide enormous variability between regions (Jones and Thornton, 2003). Under drought management conditions, a decline in maize yield of 20% for 1 °C warming is expected (Lobell et al., 2011). Average maize yield losses in Ghana are expected to be between 20% and 40%, and the area suitable for growing maize will reduce by 25–50% by 2050 [RCP8.5 or + 2 °C above preindustrial temperature] (Ramirez-Villegas and Thornton, 2015). Under current agricultural practices, maize yield in semi-arid regions in the CSV zone is expected to reduce by 9% and 23% under RCP 4.5 and between 19% and 39% under RCP 8.5 by 2069 with significant inter-farm variations in grain yield (Freduah et al., 2019).

2.3. The development of the Lawra-Jirapa CSV-SD model

The model development for Lawra-Jirapa CSV was informed by research members who spent more than two months in the CSV site, conducted systems thinking sessions with farmers and interviews with key informants, and observed CSA practices, farming activities, and wood harvesting. The model was developed using Vensim PRO software © (Ventana Systems Inc.).

2.3.1. Problem definition, model boundaries and key variables of interest

This step involves the identification of the key variables of interest and application of the CSA approach as a diagnostic tool to analyse the food system and identify trade-offs and synergies. The key variables of interest in the model (Table 1) are selected from the suggested indicators (FAO, 2017a, 2017b) to monitor progress towards the triple goals of CSA, and they are also present in the merged Causal Loop Diagram (Fig. 1.) in section 2.3.2.

The goal of a sustainable increase in agricultural productivity and income to meet the food security needs of present and future generations while considering the environment and gender equity was assessed by observing changes in maize yield, maize production in CSV site, maize gross profit, household food availability, and biomass availability. The focus is on maize, which is the most important crop cultivated in the CSV site because it is promoted through government subsidies, it replaced millet and sorghum, and thus has the most significant impact on food security (Dakurah, 2018).

The goal of adapting and building resilience to climate change assumes the introduction of context-specific, short- and long-term climate-resilient practices at household/farm and landscape scales, considering the present and future biophysical and socio-economic conditions and climate change risks. Progress is assessed by observing dynamics over time for the number of households adopting CSA soil and land management practices and hectares of land under such practices. Finally, the mitigation goal assumes that agricultural practices will reduce and remove GHG emissions throughout the food system. Progress is assessed through *GHG sequestration, GHG emissions*, and *GHG balance* at the Lawra-Jirapa CSV over time. Land-use dynamics at the CSV level indicate progress towards sustainable intensification and mitigation goals.

2.3.2. Conceptualizing the Lawra-Jirapa CSV food system

In the model conceptualisation stage, the mental models of actors in the CSV are elicited (Ford and Sterman, 1998) by engaging female and male farmers and CCAFS scientists. The CSV system is mapped in Causal Loop Diagrams (CLDs) developed in four systems thinking sessions held in the Doggoh-Jirapa village, one of the villages constituting the Lawra-Jirapa CSV. Separate systems thinking sessions were facilitated with female and male farmers, and an additional half-day session was held with CCAFS West Africa scientists. The methodological approach to conceptualize the Lawra-Jirapa food system is documented in Jagustović et al. (2019) and builds on the Systems Thinking in Practice (STiP) heuristic (Reynolds, 2011, 2016) and the Distinction, System, Relationship, Perspective (DSRP) (Cabrera and Colosi, 2008; Cabrera et al., 2015) framework.

Three corresponding CLDs that represent the distinct mental models of female farmers, male farmers, and CCAFS scientists were developed and validated (Langsdale et al., 2009). The authors analysed and merged the CLDs to the one shown in Fig. 1, consistent with the model purpose and boundary. It should be noted that the merged CLD simplifies many elements of the CSV and the food system. Nevertheless, it consolidates the important elements, interactions, and causal processes thought to operate in the system. The process of merging the mental models has the following steps (Inam et al., 2015):

(i) The female farmers' CLD serves as the basis to ensure that key variables and dynamics important for women are included. This is because, in this part of Ghana, women are responsible for most agricultural labour. Then, variables from other CLDs are integrated into this CLD.
(ii) The terminology used by different groups is aggregated and standardized, i.e., food security, food insecurity, and food gap used by different groups read "months of food availability" in the final CLD.
(iii) The merged CLD includes variables identified in at least two CLDs. A variable not included in the final CLD but mentioned in the CLD conceptualized by CCAFS scientists was included if it is

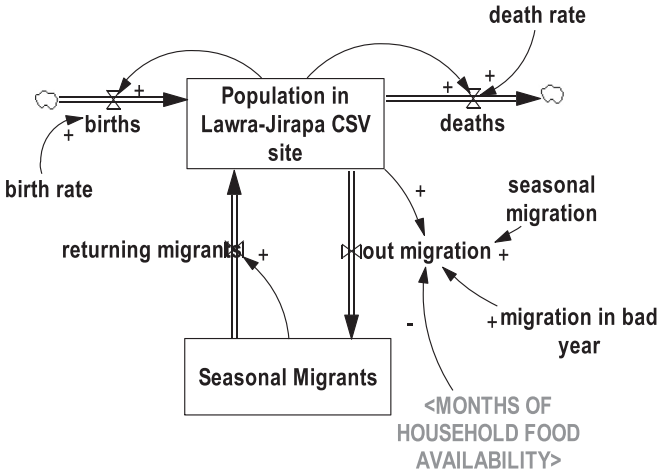

Fig. 2. The population sub-system in Lawra-Jirapa CSV.

considered as critical in the CCAFS baseline studies (2011) or other participatory site-specific relevant studies.

(iv) Interconnections between variables and/or feedback loops are included if they are identified in two CLDs or considered significant in the CCAFS baseline or other regional studies pertinent to the model purpose.

(v) Finally, to improve the alignment between model purpose and its boundaries, we iterated and added or removed variables, interconnections, and feedback loops in the merged CLD based on triangulation with data available through CCAFS baseline and midline studies and regional data.

2.3.3. *Stock and flow modelling and dynamic simulation*

In the system dynamics model, main variables are either represented by stocks or levels, which is an accumulation of quantities or historical actions measured at any point of time (e.g., human population); or they are represented by flows, the rates by which the stock variables change (Sterman, 2000; Elsawah et al., 2017) (e.g., population birth and death rates). There are also auxiliary variables operationalized in the model to increase transparency, and constant parameters operationalized with numeric values drawn from the available data.

Thus, in this stage, the CLD in Fig. 1 is converted to a stock and flow diagram (SFD) (see Figs. 2–7) that serves as the basis for simulation modelling (Richardson, 1996; Sterman, 2000). The model purpose, boundaries, and available data informed decisions on how much detail to include in the SFDs and how to handle uncertainties (Sterman, 2000). To facilitate specification of the interactions within the system boundary (Bala et al., 2017), the model was built one sub-system at a time (Figs. 2-7). Subsequently, the sub-systems were merged and simulated as one consistent model. It has six interlinked sub-models: population dynamics, biomass demand and production, land-use changes, maize production and CSA practices and technologies, maize gross profit, and GHG emissions. Significant interdependencies exist between these sub-models. The details of each sub-model are described in the following sections and in Figs. 2–7.

Population sub-system: The *population* depends on birth and death rates (Fig. 2). *Seasonal migration* occurs every year when at least one member of the household migrates. The number of household members who migrate annually increases when maize yield is low, and food is available for less than nine months per year). If the population increases, then more land is converted to agricultural land to meet the increased demand for maize.

Biomass demand and production sub-system: The *Biomass stock* depends on the *biomass demand for income-generation, total consumption for cooking,* and *biomass production* (Fig. 3). *Biomass demand* increases due to the absence of alternative energy sources for cooking for the rural and urban population, *demand from urban centres*, population growth, and the lack of mechanisms to regulate biomass use. *Biomass production* depends on the *land for biomass harvesting* that decreases with *conversion to agricultural land* through burning, and *annual woody biomass production.* The *sales of wood and charcoal* increase in years of environmental shock to cover the costs of purchasing food. The decline in biomass availability over time leads to an increase in the *land degradation rate* observed through increased erosion, with a decrease in *maize yield*, *annual maize production*, and *months of food availability*, and an increase in *seasonal migration*.

Land-use changes sub-system: *Arable Communal Land* is converted to *land for maize* as demand increases due to population increase and the rise in demand for maize as it becomes the preferred cereal (Fig. 4). The *conversion of abandoned land to land for maize* is facilitated through

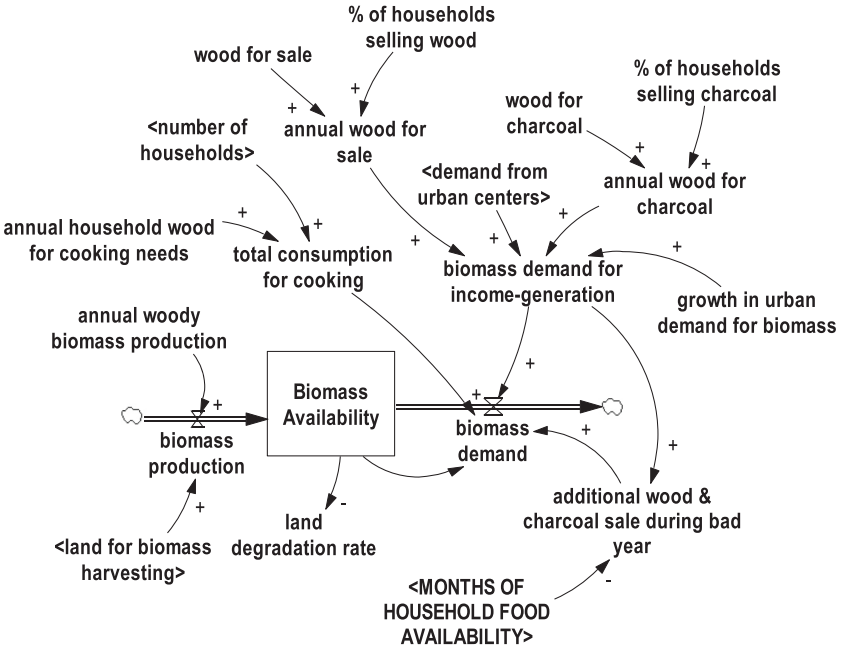

Fig. 3. The biomass availability, demand and production sub-system.

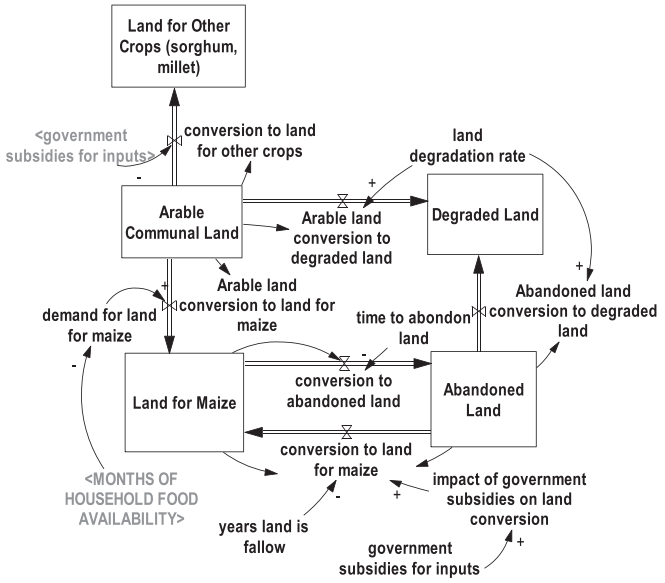

Fig. 4. The land use changes sub-system.

agricultural inputs, i.e., improved maize seeds, fertilizer, and pesticides available at a reduced price through *government subsidies for inputs*. If the preference for maize consumption continues to grow, and agricultural inputs for growing maize are available at subsidized prices, then the incentive to grow other crops declines, and the *land for other crops* does not increase. Wood is harvested from *Abandoned Land* and *Arable Communal Land*, and due to the increase in wood demand for cooking and sale, the stock of *Degraded Land* also increases.

Maize production, CSA practices and technologies sub-system: The adoption of CSA practices depends on the availability of agricultural inputs, government subsidies, and the perceived impact of practices and inputs on maize yield (Fig. 5). Together, *climate change* and *extreme events* (i.e., drought, floods, dry spells, pests), *landscape degradation*, *CSA practices* (i.e., tie ridges, crop rotation, earth bunding, reforestation, agroforestry, zai pits, drought-tolerant varieties), and agricultural *inputs* impact directly *maize production* and *maize yield* and impact indirectly *months of household food availability*. If agricultural inputs are available at a subsidized price, then their use will increase, and lead to an immediate increase in *maize yield* and *costs of production.* This *causes a* decrease in the adoption of soil and land management (SLM) *adaptation and mitigation practices* because farmers perceive such practices as taking a long time to impact yield and require more labour than the application of inputs. The frequency, intensity and impact of extreme events and the impact of climate change on maize yield increase over time with a detrimental effect on *maize yield* and *Maize Production*.

Maize gross profit sub-model: The percentage of households that use agricultural inputs, increases due to government subsidies and has an immediate impact on yield in years with good rainfall. The maize gross profit depends on the cost of hired labour, the cost of household inputs for maize, maize yield, and market maize price (Fig. 6). The household inputs costs for maize are affected by the cost of hired labour and the cost of inputs. As the use of inputs and costs of hired labour increase over time, the overall cost of maize production increases. The maize market price increases due to demand for maize, and the price increases further in years of extreme events when the yield is low.

GHG balance sub-system: The GHG net emissions balance depends

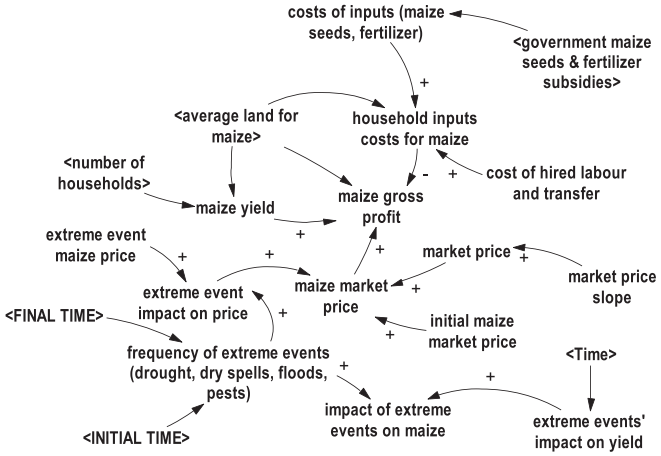

Fig. 6. The sub-system of maize gross profit.

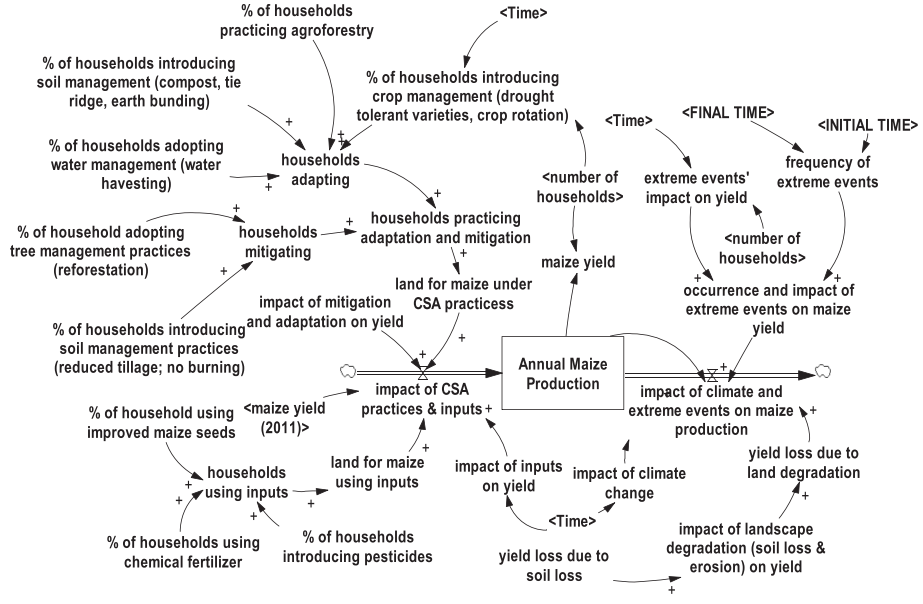

Fig. 5. The sub-system of maize production, CSA practices and inputs, and climate change and extreme events.

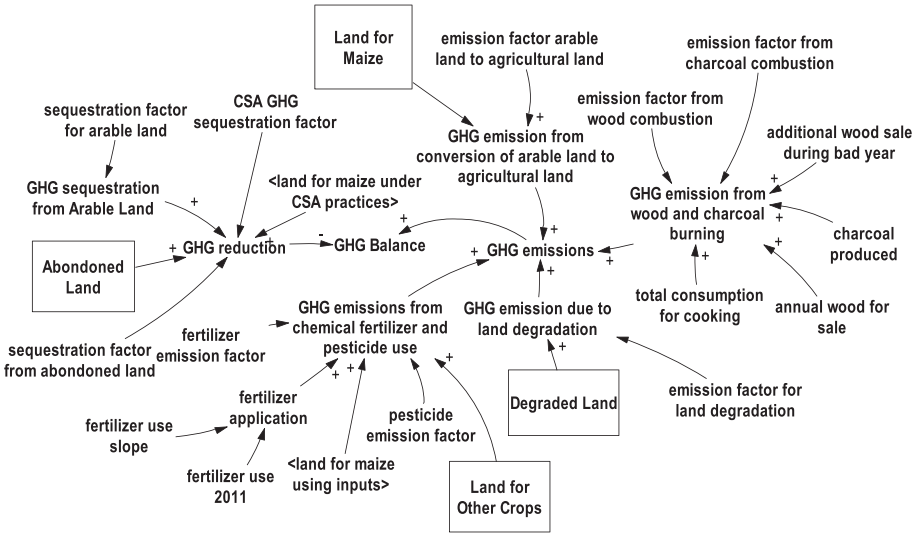

Fig. 7. The GHG balance sub-system.

on the GHG reduction and GHG emissions (Fig. 7). GHG reduction depends on the available arable communal land, land under CSA practices, and on abandoned land. GHG emissions increase due to land-use changes and wood and agricultural input use. As land is converted to agricultural land through clearing and burning, land for maize and degraded land increase and arable land decreases; these land conversion dynamics contribute to GHG emissions. In addition, as input use increases due to government subsidies, GHG emissions increase as well.

2.3.4. Data sources and model parameterization

The stock and flow diagrams described above were developed and parameterised with data from diverse sources, including information from secondary sources such as CCAFS baseline and midline surveys, government documents, journal publications (Naab et al., 2011; Nyantakyi-Frimpong and Kerr, 2015; Ndamani and Watanabe, 2016; Atuoye et al., 2017; Freduah et al., 2019; Kugbe et al., 2019; Kermah, 2020), and personal communications with farmers, CCAFS West Africa scientists, and local experts. The model was parameterised and simulated, assuming that historical agricultural, socio-economic and climatic trends will continue in the future. The model simulates the Lawra-Jirapa site for 50 years, starting from 2011 when the CCAFS research project portfolio of CSA interventions was introduced. Further information about the input data, sources, and model equations are provided in Appendix 1 and Appendix 2: Supplementary material.

2.4. Model testing and validation

Model testing and validation are crucial to establish the validity of the model structure and build confidence in model results (Sterman, 2000; Bardi, 2011; Bala et al., 2017; Amadei, 2019). Structural validity and behavioural validity tests were conducted to test and validate the model (Forrester and Senge, 1980; Barlas, 1994; Sterman, 2000). The structural validity test ascertains whether the structure of the model reasonably captures the actual relationships that exist in the system being modelled. The behavioural validity test evaluates the model's ability to replicate the dynamic patterns of the real system. These model tests were continuous during the modelling process.

2.4.1. Structure validity tests

A boundary adequacy test was carried out to ascertain whether the model includes the major variables, processes, and relationships necessary to explain the behaviour of the system. The authors conducted the test in consultation with expert stakeholders within the system. This resulted in adding *government subsidies* and *urban demand for biomass* to the model structure.

Dimensional consistency was conducted in the model through the built-in "units check" and "model check" Vensim functions, and the model is found to be error-free. The integration error test assessed whether the results are sensitive to the choice of the simulation time step. The time step of the model was reduced progressively from 1 to 0.0625 years until its value made no significant numerical change to the simulation results. Extreme condition tests were performed to evaluate the robustness of the model and uncover structural flaws through observing model behaviour under extreme conditions.

The direct structure test assessed the model structure against the real system and, thus, the usefulness of the model with regard to its intended purpose and use (Sterman, 2000): to understand the food system behaviour in the CSV and identify and understand how synergies and

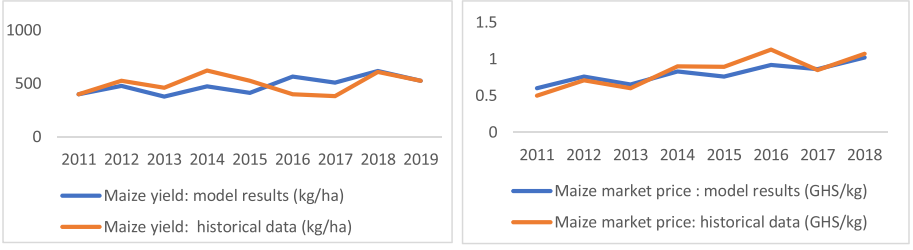

Fig. 8. Historical data and simulated results for maize market price and maize yield.

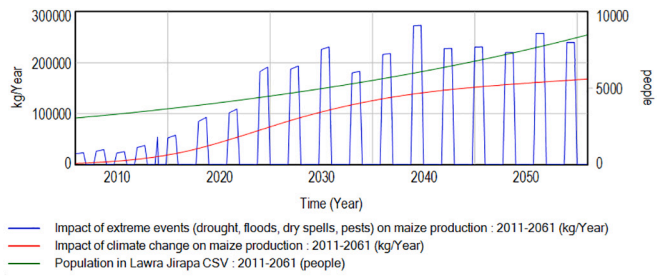

Fig. 9. Population trend and impacts of climate change and extreme events on maize production (2011–2061).

trade-offs unfold temporally at the household and landscape scale. Furthermore, the adjustment of the model scope and variables throughout the modelling process and engagement with farmers and CCAFS scientists ensured that model output depicts the real situation. In addition, the model structure was also assessed with respect to the conceptualization stage, the CLDs and the available knowledge and data. We analysed assumptions and causal relationships, considered the model purpose and boundaries, and revised the model structure accordingly. A further test was presenting the final model results to the CSA and food security experts to verify whether the results correspond to the expert's intuitive understanding of the system.

2.4.2. *Tests of model behaviour*

The behaviour validation tests looked at the degree to which the model reproduces the past and present dynamic patterns (i.e., frequency, trends, lags) observed in the Lawra-Jirapa CSV, rather than on exact point-in-time prediction. The authors used available historical time series data to assess the model's ability to reproduce the observed patterns. The initial results produced by the model for 2011 were verified through the CCAFS baseline studies, and 2017 model behaviour was verified through CCAFS midline studies. Other available studies and secondary data were consulted to compare model behaviour with data available for specific points in time for the same variable. Fig. 8. compares the observed and simulated trends of some key variables of the model for which historical data was available over the calibration period. The results show that the model can reproduce system behaviour.

A workshop with CCAFS scientists and experts in SD and food systems was conducted to review the output behaviour for the key variables of interest and evaluate whether the model produces the pattern of behaviour observed in the site and documented in the studies for the right reasons.

A series of sensitivity analyses were performed to examine the impact of variations in parameter values on model behaviour and provide a measure of the reliability and validity of the model and its outputs. This was performed by setting the sensitivity simulation set-up tool at 400 runs, and the random variable distribution. The first sensitivity test was performed separately on the following parameters:

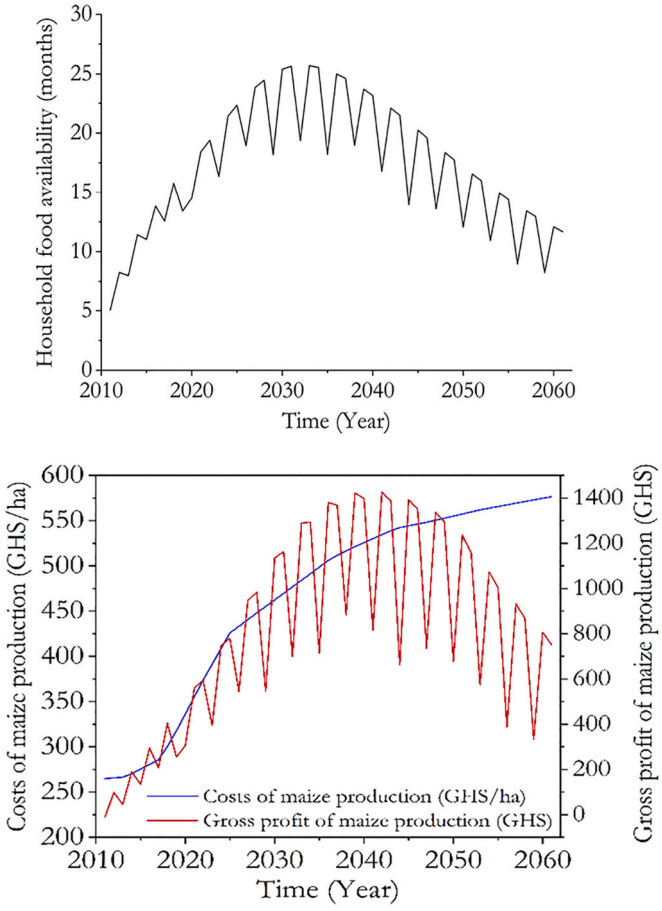

Fig. 10. Simulation results for 2011–2061: months of household food availability (top), maize production costs and gross profit of maize production (bottom).

(i) The *birth rate* parameter value was set at 30.2 births/1000 persons. For the sensitivity test, the minimum birth rate parameter value was set at 10 births/1000 persons and the maximum at 40/1000 person.
(ii) The parameter *% of households selling charcoal* was set at 55%. For the sensitivity test, it was given values of 0% - 90% maximum, indicating a decline or increase in the urban demand for biomass.

The sensitivity output parameters were *Biomass Availability*, *Degraded Land*, *Production in CSV*, and *Land for Maize*. The results of the tests led to structural changes and a review of equations and functions to address the unexpected behaviour. The second sensitivity test was performed on the variables suspected to have markedly different or uncertain evidence bases (Chapman and Darby, 2016) to investigate the potential to confound the overall confidence in the model results.

(i) For the parameter *climate change impact slope,* the impact on maize yield was set to increase 0.04 per year (amounting to 25% reduction in maize yield by 2061). As climate change models predict an impact of up to 55% decrease in maize yield, the minimum parameter value was set at 0 and the maximum at 0.05 (i.e., 55% reduction in maize yield by 2061).
(ii) The parameter *maize yield 2011* set at 300 kg/ha, was set at 200 kg/ha minimum and 1200 kg/ha maximum value (Fig. 9. top). The studies consulted to operationalize and validate the model report the lowest maize yield on smallholder farms in the UWR as compared to the rest of Ghana, ranging from 280 kg/ha in 2011 to 525 kg/ha 2019 (Kermah, 2020) and 500–1200 kg/ha with recommended fertilizer application (Bua et al., 2020).

The sensitivity output parameters were *maize yield, maize gross profit,* and *months of household food availability*. Repeated sensitivity tests on the same parameters generated behaviour that corresponded to the expected sensitivity of the real system.

3. Results

The following sections present simulation results for the key variables of interest. The population in Lawra-Jirapa CSV (Fig. 9., red line) will continue to grow based on the current birth rate of 3% per year and will increase from an estimated 3000 people in 2011 to 8450 by 2061. The expected decrease in rainfed maize yield in Ghana is between 25% (under A1B scenario; CNRM-CM3 GCM, CSIRO-MK3 GC, ECHAM5 GCM) and 40% by 2050 [RCP8.5] (Ramirez-Villegas and Thornton, 2015). We implement a gradual reduction of 25% by 2061 in the model. The frequency of extreme events, i.e., drought, dry spells, floods, or pests in the CSV site was modelled based on historical data (2011 to 2020) and post-2020, with one event every three years. The impact of extreme events on maize production in the CSV site (Fig. 9, blue line) is modelled to increase in intensity, i.e., 15% yield reduction in 2011, increasing to 35% by 2061. Climate change will result in an estimated loss of 2500 kg/year in 2011 to 167,000 kg/year by 2061 (Fig. 9, green line). The frequent fluctuations in the maize production loss in the CSV are attributed to extreme events, and increased losses in years of shocks from 25,000 kg/year in 2011 to over 257,000 kg/year by 2061. This increase is attributed to a rise in land for growing maize that increases maize production and due to extreme events and climate change that increase in intensity. Similar results to these are reported in studies conducted in northern Ghana (McSweeney et al., 2008; Antwi-Agyei

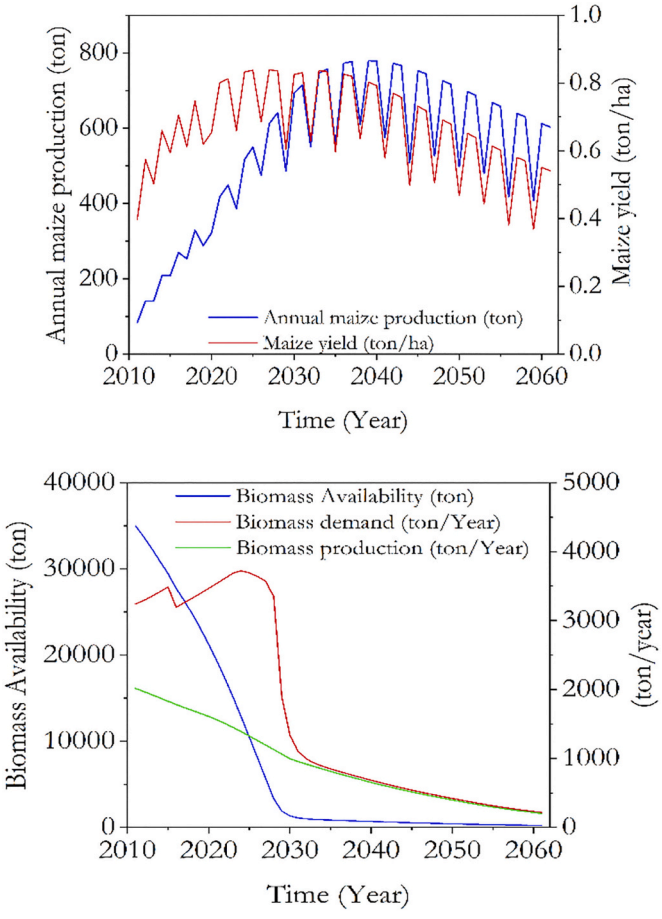

Fig. 11. Simulation results for 2011–2061: maize yield and production (top), and biomass availability, production, and demand (bottom).

et al., 2012; Challinor et al., 2014; Deryng et al., 2011; Sultan and Gaetani, 2016; Freduah et al., 2019). These studies look at the impact of climate change, adaptation, and intensification and conclude that there is little evidence for the potential to avoid maize yield loss.

3.1. Sustainable increase of agricultural productivity and income

Progress towards increasing production and income is assessed through changes in *maize yield*, *maize production in the CSV site, maize gross profit, household food availability,* and *biomass availability* (Figs. 10 and 11). The model results show an increasing trend in household food availability from just six months in 2011 to 12 months in 2019, with a reduction in food availability in years of extreme events. The CCAFS baseline and midline survey report similar results for household food availability. 46.2% of households reported being food insecure for 3–4 months by 2017 compared to 42% in 2011, while 33.3% of households reported being food insecure 5–6 months by 2017 compared to 38% in 2011 (Naab et al., 2011; Ouedraogo et al., 2019; Kermah, 2020). Months of household food availability will continue to increase (Fig. 10, top), so that household food availability needs will be met by 2020 and will peak by 2030, when households are expected to produce a surplus of 5–13 months of maize on average. Post-2035, maize surpluses will reduce from 24 months to 12 months by 2061 in years without extreme events. In years when extreme events occur, household food availability will reduce from 18 months in 2035 to only 8 months by 2061. The gross profit of maize production (Fig. 10, bottom, red line) was calculated based on total household maize production, costs of maize production considering agricultural input costs (Fig. 10, bottom, blue line), and maize market price. The model shows an increase in maize production cost due to an increase in the use of inputs and an increase in the average maize gross profit from 270 GHS per household in 2019 to above 1300 GHS by 2030 due to an increase in maize yield and subsidized input prices. However, an extreme and frequent reduction in maize gross profit due to extreme events shocks is observed post-2030, and that gross profit is expected to decline to below 361 GHS by 2061.

The model shows an increasing trend in annual maize production at CSV level from 2011 to 2030, when it stagnates at an estimated 892 ton, characterized by a frequent reduction in production (Fig. 11, top, blue line). The average maize yield will increase by 2023 from 0.380 ton/ha in 2011 to over 0.8 ton/ha due to increased use of agricultural inputs (Fig. 11, top, red line). The impact of fertilizer on maize yield will be minimal compared to other agro-ecological zones, due to poor soil quality and reduction in the adoption of CSA adaptation and mitigation practices. The increasing trend is characterized by frequent variability and reduction in maize yield in years of extreme events. From 2035, a downward trend with frequent variability is observed due to extreme events and climate change impact, and by 2061 the average maize yield is expected to fall to 0.53 ton/ha and in years when extreme events occur to 0.36 ton/ha, which is far below the national target of 4.5 ton/ha. A decreasing trend in biomass availability (Fig. 11, bottom, blue line) is observed due to the growing demand for woody biomass from urban centres and rural households and a reduction in biomass production due to overharvesting and converting more arable communal land to land for agriculture. Demand for woody biomass continues to increase due to a lack of alternative sources of energy for increasing rural and urban populations. The downward trend in biomass demand post-2027 is observed due to a decline in biomass availability for income-generation. The demand for biomass will exceed availability by 2030 provided that no alternative energy source is available for rural and urban households.

3.2. Adaptation and resilience to climate change

The number of households that adopt labour-intensive CSA adaptation practices declines over time from an estimated 260 households to about 160 households by 2025 (Fig. 12, blue line). The number of households using agricultural inputs grows exponentially due to government subsidies and the perceived immediate impact of inputs on maize yield (Fig. 12, red line). There is also stagnation in the land under labour-intensive CSA adaptation practices offering simultaneous adaptation and mitigation benefits, due to government subsidies with perceived higher impact on yield (Fig. 12, green line). Land for maize using agricultural inputs increases exponentially due to government subsidies and an increase in conversion of land for growing maize (Fig. 12, grey line).

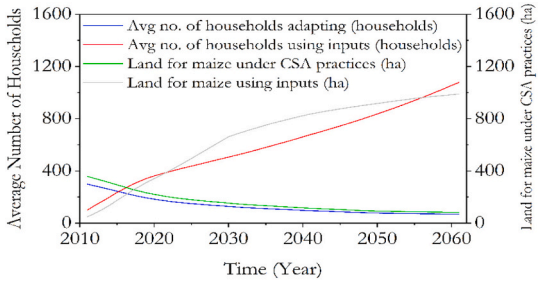

Fig. 12. Adaptation and resilience to climate change 2011–2061: land under adaptation CSA practices and using inputs, and number of households adopting CSA practices and using inputs.

3.3. GHG emissions reduction

GHG reduction in Lawra-Jirapa CSV has a declining trend (Fig. 13, top, green line) due to a reduction in the number of households adopting mitigation practices (Fig. 13, bottom, blue line), an increase in the conversion of land to agricultural land through slash and burn practices, and the demand for land for maize that results in a reduced number of years land is left fallow to sequester GHG. The number of households that adopt mitigation practices and land under mitigation exhibits a downward trend. GHG emissions show an upward trend (Fig. 13, top, red line) due to an increase in biomass use, an increase in conversion of arable land (i.e., Guinea Savanna agro-ecological zone) to agricultural land, and an increase in agricultural inputs use. GHG emissions reduce in years when households produce enough maize and thus sell less wood and charcoal to meet food security needs. The estimated GHG balance in Lawra-Jirapa shows an increasing trend from −117,000 tCO_2e/year in 2011 to 49,000 tCO_2e/year by 2061. By 2038, the GHG emissions will exceed GHG reduction potential and result in a positive GHG balance in Lawra-Jirapa. This is consistent with Leitner et al. (2020), who find that increasing maize yield in sub-Saharan Africa through increasing N fertilizer application rates is expected to triple current maize yield while increasing soil N_2O emission by almost sevenfold.

Land-use changes (Fig. 14) have an impact on removing GHG emissions, climate adaptation, resilience, and sustainable intensification goals. The land for growing maize (grey line) increases due to increased demand from the growing population and government input subsidies. The land increase for maize leads to an increase in production and an increase in GHG emissions from agricultural activity. Land for growing other crops (black line) decreases from 650 ha to an estimated 370 ha by 2061, indicating a reduction in crop diversity with an impact on climate adaptation and resilience goals. Similar results for agricultural product diversity for 2011 and 2019 are reported by CCAFS baseline and midline survey showing that the agricultural product diversity index declined, and, by 2019, only 14% of households were producing 9 or more products (high diversity) as compared to 46% in 2011, while 31.4% of households were producing 1–4 products (low diversity) as compared to 1% in 2011 (Naab et al., 2011; Ouedraogo et al., 2019). The increasing trend in degraded land (green line) and conversion to land for growing maize (grey line) result in a decrease in available arable land (red line), leading to a reduction in GHG sequestration and an increase in GHG emissions.

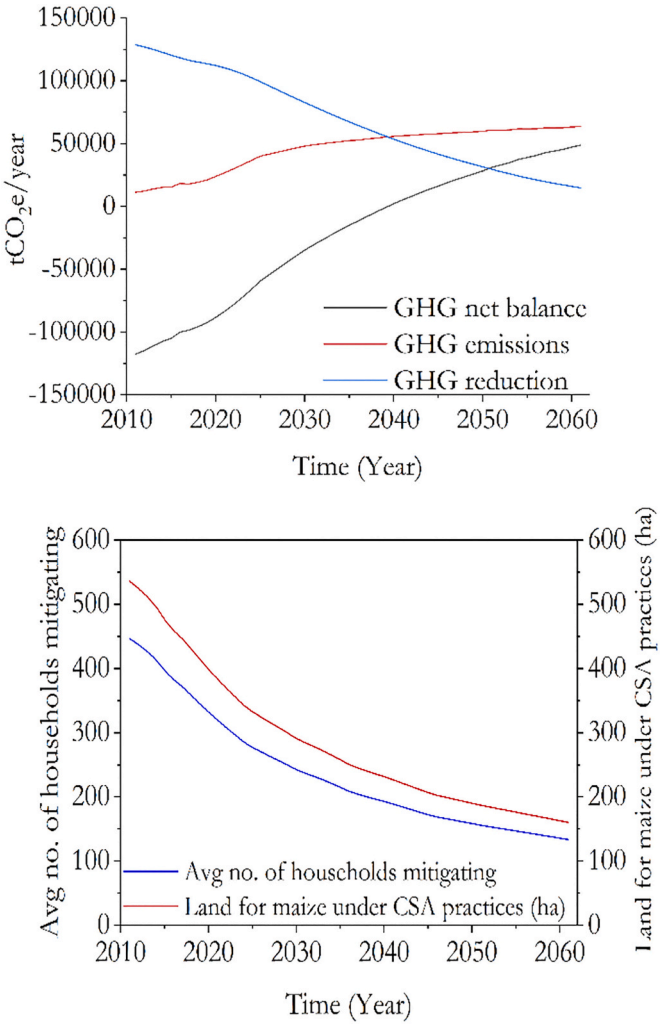

Fig. 13. Removal of greenhouse gas emissions 2011–2061: GHG emissions, reduction, and balance (top), and households practicing mitigation, and land under mitigation practices (bottom).

4. Discussion

The model results reveal the trade-offs and synergies across the entire food system within each CSA goal and between CSA goals. The key variables of interest indicate how the system evolves over time.

4.1. Synergies and trade-offs within CSA goals

The results indicate progress towards a sustainable increase in production and income and improvement in household food availability.

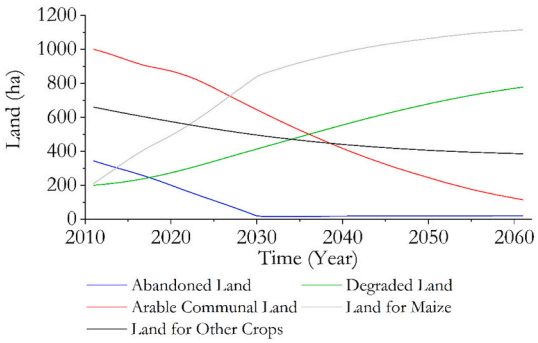

Fig. 14. Land-use changes in CSV Lawra-Jirapa in 2011–2061.

Synergies between maize yield and agricultural productivity are observed in years with no extreme events. Biomass harvesting declines in years when food is available. However, the long-term upward trend in biomass demand eventually exceeds the carrying capacity and leads to land degradation. The synergies between the variables conducive to the goal of sustainable increase in production and income will dominate until 2035, when trade-offs emerge and result eventually in less than ten months of household food availability by 2055 (Fig. 10, top). The land-use change dynamics indicate the short-and long-term trade-offs that arise in sustainable production (Fig. 14). In the short term, the conversion of arable land to land for maize increases due to low yield and demand for maize. In the long-term, degraded land increases due to biomass harvesting for cooking and sale. An increase in the CSV's degraded land results in erosion and poor soil quality at the farm level, with a delayed impact on reducing maize yield (Fig. 11, top). This causes an increase in the conversion of abandoned and arable land to agricultural land. Other studies report the same dynamics in the region, observed through an increase in agricultural and degraded land (Kanton et al., 2016) and yield losses as high as 39.56 kg/ha/year in maize crops, equivalent to 2.6% of the current yield level (Diao and Sarpong, 2007).

Post-2017, the increase in the use of agricultural inputs (Fig. 12) leads to an increase in maize yield and production. At the same time, the increase in input use leads to an increase in maize production costs (Fig. 10, bottom). However, the cost of maize production and the loss of maize yield in years with extreme events lead to variable maize gross

profit. The increase in maize production is not a sustainable path to long-term income increase and poverty reduction in northern Ghana, as it depends on maize input subsidies. The synergies between key indicators of sustainable increases in agricultural productivity and income are observed in the short term in years with no extreme events. Post-2035, frequent extreme events and climate change will reduce maize yield and household food availability and compromise long-term food security from maize production (Figs. 10, top and 11, top). A focus on intensification and expansion of agricultural land productivity through high-input labour-saving technologies results in only marginal maize yield increase (see Houssou et al., 2016). Furthermore, maize production with chemical fertilizer application in the UWR region is not always profitable and sustainable considering soil conditions and climate variability (Vondolia et al., 2012; Baba et al., 2013; AGRA, 2017; Buah et al., 2017; Ragasa et al., 2018; Kankam-Boadu et al., 2018; Scheiterle et al., 2019; Bua et al., 2020). The implication is that other measures, such as soil and water conservation, should be practised simultaneously.

Key variables of interest to monitor progress towards the goals of adaptation and resilience to climate change reveal trade-offs observed in the decreased number of households adopting CSA adaptation and mitigation practices that require labour. The results show short- and long-term trade-offs in relation to the goal of emissions reduction due to land conversion to agriculture and increased use of biomass and agricultural inputs. Inputs use leads to trade-offs as farmers expect an immediate impact on yield and therefore are less motivated to adopt mitigation practices that have delayed impact on yield increase and contribute to GHG reduction and sequestration.

4.2. Synergies and trade-offs between CSA goals

The model results indicate that the dynamics between the elements within and outside the CSV site lead to short-term progress towards the productivity and income goal, trade-offs in GHG emissions reduction, and the achievement of the climate adaptation and resilience goal in the long term. GHG emissions increase because of increased land conversion to agriculture, biomass use, and agricultural inputs use that produce GHG emissions exceeding sequestration rates by 2028 in the CSV. The variability and downward trend post-2035 of maize yield, maize production, and maize gross profit indicate trade-offs related to the goal of climate adaptation and resilience. Increased use of inputs through the government subsidies programme leads to a short-term growth in maize yield but only in years with no extreme events. The increase in climate risks and extreme events reduces the effectiveness of inputs, indicating that adaptation practices and maize promotion technologies will not effectively address these risks in the long term. A recent review of the input subsidy programmes in seven countries, including Ghana, reports results similar to our model and concludes that chemical fertilizers quickly raise national food production, household grain yields, and production levels, at least in the short term (Jayne et al., 2018; Theriault et al., 2018; Vercillo et al., 2020). These studies and our model call for caution when developing national-scale policies, as crop response to fertilizer is lower than expected on smallholder managed fields and short- and long-term crop responses to fertilizer vary across agro-ecological regions.

The goal of increased production is prioritised in the Lawra-Jirapa CSV due to the national subsidization programme. Hence, as an element outside the CSV boundary, the national subsidy programme impacts dynamics and causes trade-offs and synergies at the CSV level. Our model and empirical studies show that the increase in the availability of fertilizer, improved maize seeds and pesticides, all at a subsidized price, and increase demand and preference for maize consumption (Dakurah, 2018) result in a shift towards maize production and a reduction in crop and dietary diversity (Ouedraogo et al., 2019). These effects compromise long-term synergies with the climate adaptation and resilience goal. Our model and other studies (Nyantakyi-Frimpong and Kerr, 2015; Hengsdijk et al., 2015; Mangnus and Westen, 2018; Vercillo et al., 2020) show that a focus on maize production—after an immediate increase in yield and income—will not bring long-term food security, and that dependence on the crop will increase CSV vulnerability.

The trade-offs and synergies within and between goals point to the "fixes that fail" archetype (Kim and Anderson, 1998; Clancy, 2018). Solutions or "fixes" implemented to alleviate the symptoms of climate change vulnerability (i.e., low maize yield, low maize productivity, frequent loss of yield, poverty) result in short-term synergies that alleviate the symptoms (e.g., improved yield, production, household food availability). However, over time, the solutions produce unintended consequences, observed as trade-offs, (e.g., biomass overharvesting, increase in agricultural land and GHG emissions, short-term adaptation and resilience outcomes). Post-2035, reductions in yield and food availability cause the original problem symptoms to return to their initial levels or become worse. Continuous application of the same or similar "fixes" leads to a "better before worse" situation, as our results show. The results highlight that: (i) the current food system in the CSV is not resilient to future climate change, extreme events, and socio-economic changes, and (ii) any short-term" fix" should be implemented in conjunction with efforts to redefine the purpose and structure of the food system and bring about a paradigm shift resulting in transformational changes.

A shift in farmers' shared ideas, tacit assumptions, and beliefs about the food system in Lawra-Jirapa could result in a paradigm shift and create opportunities to revisit the food system goals and its structure. Systems thinking tools can facilitate a paradigm shift by showing stakeholders a different long-term perspective of the system and enable them to see the system as a whole. The goals of the Lawra-Jirapa food system reflect the current household food availability and income needs that rest on agriculture dominated by maize production. The current driving forces in the food system emerge from reinforcing feedback loops that increase productivity and income in the short term, pushing the system behaviour in one direction.

At the same time, the long-term survival of the system, considering maize performance post-2035, potentially rests on environmental health and livelihood diversification, which could be a critical balancing loop to reduce future risks to extreme shocks. Weakening the short-term, dominant reinforcing feedback loops would reinforce and strengthen the long-term balance feedback loop, and potentially lead to climate-smart livelihoods diversification and a halt to environmental degradation. For example, this could be done by removing subsidies for inputs or by a combination of tying input access to compulsory sustainable land management practices while removing urban demand for biomass. These are some possible interventions from the study and observed trade-offs and synergies that could be tested through the model.

4.3. Future model applications

This SD model can be used to analyse, monitor, and evaluate interventions in complex food systems. In this study, the Lawra-Jirapa SD model is used as an exploration tool to identify trade-offs and synergies and inform the identification of policies and practices to be tested. The model is ready to be used, with minor structural and parameter changes, to investigate the food systems in CSVs in other African countries and identify trade-offs and synergies that could inform these systems' sustainable transformation. In the future, the model will be used to test alternative scenarios, management actions, and ideal leverage points to achieve the triple goals of CSA across food systems in the short- and long-term. Regarding designing CSVs and monitoring progress towards the triple goals, the model will be employed to support the development of a dynamic theory of change for CSA and to address gaps in the use of systems tools to monitor and evaluate the performance of complex food systems.

The future model applications and SD modelling efforts in other CSV sites should also consider the challenges of SD modelling, particularly

concerning the qualitative and quantitative stages of the modelling process. For instance, the systems thinking sessions in the conceptualization stage uncovered the CSV mental models of farmers and CCAFS scientists. However, the complete merger of different mental models into the final CLD diagram is a challenge. While CSA experts reviewed our final model to gain confidence that it represents the structure and observed behaviour of the situation in the CSV, farmers were not involved in the review of the final merged model. Engaging farmers in the review of the merged CLD could lead to the identification of other potentially essential interconnections that would offer additional insight into the system dynamics, including resistance to change the current food system and resistance to adoption of CSA practices.

In addition, transferring the CLD into the stock and flow diagram called for various modelling decisions to be made by the authors about the operationalisation of "soft" variables, the behaviour of key variables, and the availability of input data. The model formulation stage included a review of published studies, reports, and scientific papers that were sometimes limited and conflicting (e.g., maize yield at the national level and as reported by independent studies focusing on smallholder maize yield in UWR or the CSV site). This called for an extensive literature review to support the model development and validate its structure. The authors had to decide which data to use or ignore based on the observed dynamics for key variables in Lawra-Jirapa. Data challenges could potentially be avoided by employing a systems perspective to the design of the CSA baseline studies for CSV sites that would support the use of systems tools to understand dynamics between elements of the food system. Considering the above potential limitations, the view of system dynamics experts and the authors in the study is that the model should be assessed not based on its accuracy, but on its "usefulness with respect to the purpose" (Sterman, 2000; Elsawah et al., 2017).

5. Conclusion

The transformation of food systems through the CSA approach can help attain multiple SDGs, provided that the trade-offs from the introduced practices, policies, and technologies are mitigated and their synergies are promoted. In practice, site-specific conditions, CSA goal prioritisation, and the complex adaptive nature of food systems pose challenges to the identification of synergies and trade-offs. In this study, we develop an SD model to investigate the behaviour over time of key variables that track progress towards the triple CSA goals across the entire food system. The simulation of food system dynamics under the current CSA practices and technologies, population growth, extreme events and climate change impacts, and government policies reveals short-term progress towards the goals of increased productivity and income, with trade-offs in the goals of GHG mitigation and climate adaptation and resilience.

However, post-2035, trade-offs are observed in all three goals. The emergent system behaviour exhibits a "better before worse" pattern with short-term synergies that points to the underlying "fixes that fail" archetype. As a result, the short-term progress towards the goals is reversed, and trade-offs emerge due to unintended consequences and delays, causing the original problem symptoms to return to their previous level of intensity or worse. Thus, to sustainably transform food systems, the CSA approach should simultaneously consider progress towards all three goals across the food system and identify and mitigate trade-offs in the short and long terms. In view of the present and future dynamics in the Lawra-Jirapa CSV site, establishing a sustainable food system calls for transformational changes that alter the current food system's purpose and structure.

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.

Acknowledgement

This work was implemented as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), which is carried out with support from the CGIAR Fund Donors and through several bilateral funding agreements (the CGIAR Fund Council, Australia-ACIAR, European Union, International Fund for Agricultural Development-IFAD, Ireland, New Zealand, Netherlands, Switzerland, USAID, UK, and Thailand). For details, please visit https://ccafs.cgiar.org/donors. We thank women and men farmers in Doggoh-Jirapa and CCAFS scientists for participating in the systems thinking sessions and the staff of the CSIR-SARI and of the Ministry of Food and Agriculture Department in Jirapa for providing logistical on-site support and translation services during the field data collection.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103131.

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