A SYSTEMS APPROACH TO ANALYZE HOUSEHOLD VULNERABILITY TO FOOD INSECURITY IN RURAL SOUTHERN MALI USING A SPATIALLY-EXPLICIT INTEGRATED SOCIAL AND BIOPHYSICAL MODEL

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ABSTRACT

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Mali is expected to be profoundly impacted by climate change. Its mid-century temperature could increase by 2°C, which could have detrimental impacts on crop production. Besides, northern Mali is currently highly arid and is not suitable for agriculture. The South has the responsibility to feed the national population. However, the region is experiencing rapid population growth. Mali is likely to struggle to feed its growing population under climate change. Food production and food security in the South have a wider influence on the national food supply. Food security lies at the interface of biophysical, climatic, and socio-economic systems and demands a systemic approach for evaluation. Using a biophysical crop model with an agent-based model of household food systems, we capture the dynamics within and across multiple associated systems. We focus in the South and use multidisciplinary tools to explore the trajectories of household food security under climate change and population growth in the region.

The dissertation is organized into three research papers. Paper 1, entitled "A Largely Unsupervised Domain-Independent Qualitative Data Extraction Approach for Empirical Agent-based Model Development.", focuses on exploring household food systems and identifying actors of household food security and their behaviors. Chiefly, we aim to extract the information needed to develop an ABM of household food systems. We apply largely automatic efficient approaches for information extraction from contextually rich qualitative field narratives. Using a combination of semantics and syntactic Natural Language Processing, we identify actors (agents) of household food security, their properties, and actions and interactions responsible for household food supply. The data extraction is primarily unsupervised and, apart from being efficient, it controls manual manipulation and bias introduction in the model development. We use the extracted information

for developing a contextual model of household food security. Finally, we subject the model to stakeholder evaluation for credibility and validity.

Paper 2, entitled "Analyzing household vulnerability to food insecurity in rural southern Mali - a coupled biophysical and social model approach.", combines a biophysical process-based crop model with an ABM of household food system to analyze household vulnerability to food insecurity in southern Mali. We use the Systems Approach to Land Use Sustainability (SALUS) as the crop model to simulate the cultivation of maize, millet, and sorghum in the region. While SALUS provides information on food production, ABM simulates interactions for food access. We measure household vulnerability using Food Security Vulnerability Index (FSVI), a coping-based index, that evaluates households' vulnerability to food insecurity by assessing the mechanisms used by the households to address household food scarcity. Running a business-as-usual scenario, defined by low access to input, high population growth, and a high emission climate change scenario at Representative Concentration Pathway (RCP) 8.5 level, we find that maize and sorghum lose their productivity significantly under future climate change. Besides, the region sees a significant increase in its food insecure population. Around 80% of the regional households are at risk of food insecurity by mid-century.

In paper 3, entitled "Global or Local? Effects of policy interventions on household food security in Koutiala, southern Mali: A coupled biophysical and social systems approach.", we evaluate the effectiveness of selected global and local level policy intervention in promoting household food security in the South. The model recommends local level interventions that include improved access to input and lower population growth for a prompt and significant increase in food security in the region. More than 60% of the regional households could be food secure under the combinations of the interventions. However, the global level intervention that consists of lowering emission to RCP4.5 level does not have significant impacts on local household food production and food security.

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CHAPTER 1

INTRODUCTION

1.1 Background

Unlike many countries in the world, Mali could not seize the benefits of the Green Revolution. The development and application of improved technology and farm management, that were necessary for a successful Green Revolution, were severely inadequate (Otsuka and Muraoka 2017). As a result, farmers in the region could not intensify their agriculture (Brown, Hintermann, and Higgins 2009), and their productivity remained stagnant for decades (Djurfeldt et al. 2005). The current farming practices in Mali are still very traditional. Conventional hand tools, low-yielding cultivars, and poor application of inputs are quite ubiquitous (Brown, Hintermann, and Higgins 2009). Consequently, its crop productivity remains amongst the lowest in the world. The future of Malian agriculture does not look promising either. The country is expected to be profoundly impacted by climate change. Climate models used by the Intergovernmental Panel on Climate Change (IPCC) unanimously predict a warmer climate in Mali (Traore et al. 2013). High temperature has detrimental effects on crop productivity (Asseng et al. 2017; Basso, Kendall, and Hyndman 2013). As a result, the region may see a further decline in its crop production. With some models predicting increased rainfall, Mali can expect to see improved production in the future (Patricola and Cook 2010; Sultan and Gaetani 2016). However, the increased frequency of erratic rainfall and a warmer climate expected under climate change may nullify such benefits (Sivakumar 1988).

Mali has four broad bio-climatic zones (Figure 1). The northern half of Mali is highly arid and unsuitable for agriculture. People living in the North are generally nomadic; their livelihood depends on trans-Saharan trades. They rely entirely on food imports. The country becomes wetter and more productive in the South. The Sudano-Guinean zone receives more than 1000mm of annual rainfall (Traore et al. 2013). Due to the relative abundance of fertile land, people in the South are more involved in agricultural activities. The region is the primary exporter of food in

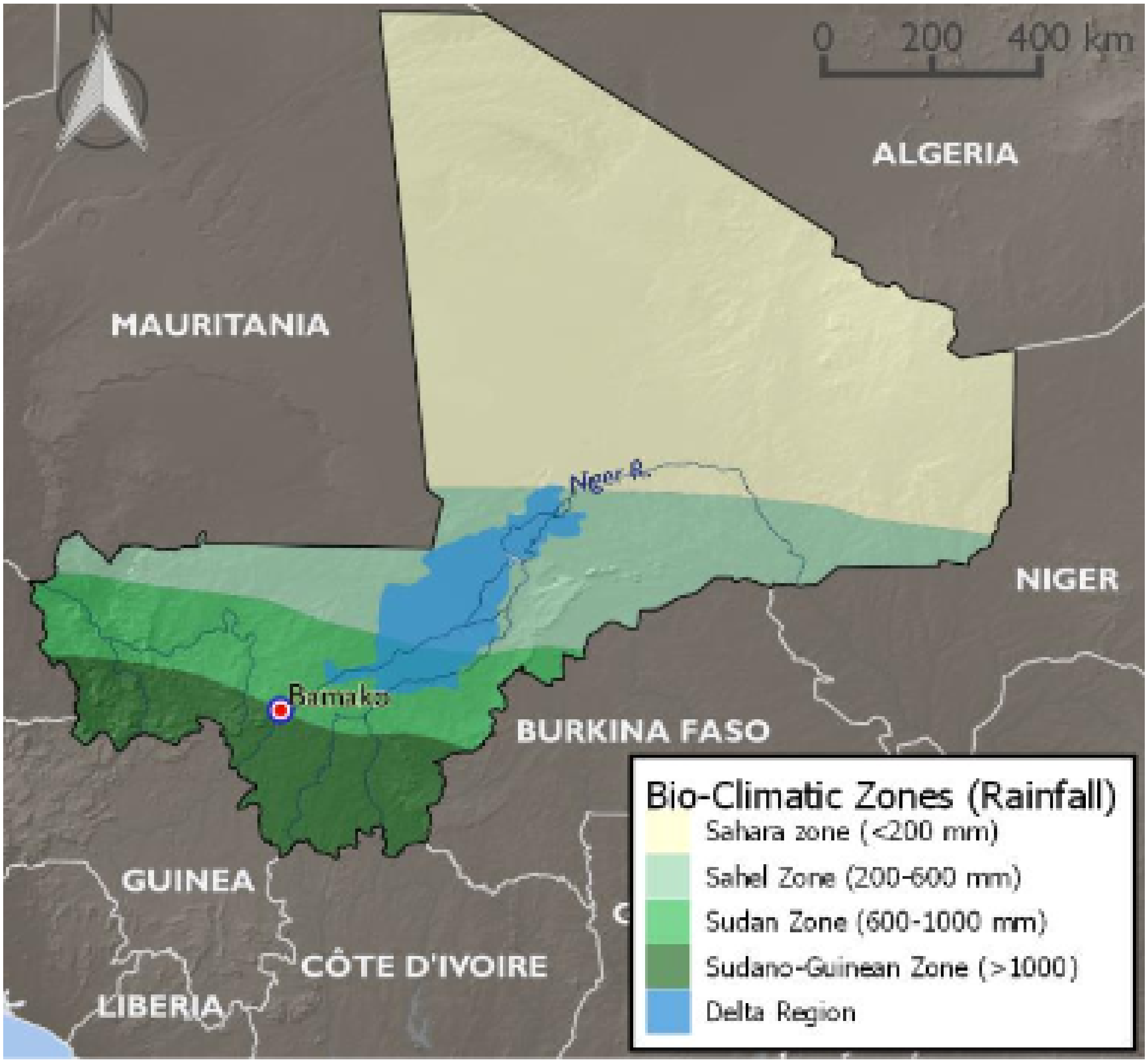

Figure 1.1: Bio-Climatic Zones of Mali. Source: https://www.climatelinks.org/

the nation. However, the regional farmers are predominantly poor and into subsistence farming. Intensification in the region is highly limited due to inadequate access to technology and resources. Furthermore, soil degradation is omnipresent (Adger et al. 2001) in the region.

Mali is experiencing rapid population growth (Farvacque-Vitkovic et al. 2007; Dijk, Bruijn, and Beek 2004). With the current state of farming in the South, the country will face difficulties feeding its growing population. The South has a daunting task of feeding its people while maintaining food supply to the nation. Household food security here has broader implications for the national

Figure 1.2: Koutiala: the study area

food supply. The purpose of this study is to explore household vulnerability to food insecurity from climate change and population growth in rural southern Mali. In this study, we explore the trajectories of household food security in Koutiala, a region in rural southern Mali (Figure 2). Koutiala makes a significant contribution to the national food supply and is regarded as the breadbasket of the country (Bingen 1998). Using a systems approach, we look at household food systems in the region. Additionally, combining multidisciplinary approaches, we explore their trajectories under climate change and population growth and evaluate the efficacies of selected policy interventions in promoting food security in the region. Household food security in rural Mali mainly relies on household food production and access. Food production responds to biophysical and climatic factors and farm management. Food access, on the other hand, is affected by resource availability and social norms and practices. In other words, food security lies at the intersection of biophysical, climatic, and socio-economic systems and, therefore, demands a systems approach for its analysis (Jones et al. 2017). In this study, we integrate a bio-physical crop model with an agent-based model (ABM) developed using field narratives of household food systems to evaluate vulnerability to food insecurity. The crop model incorporates the dynamics within biophysical and climatic systems for estimating household food production while the ABM explores social interactions contributing to household food access.

Vulnerability to food insecurity is governed by complex interactions between the associated dynamic systems. Vulnerability measurement needs to capture the dynamics of the complex systems (Krishnamurthy, Lewis, and Choularton 2014). In this study, we measure household vulnerabilities using a coping-based Food Security Vulnerability Index (FSVI). FSVI evaluates vulnerability by exploring household coping mechanisms. Households start to cope when faced with food scarcity at home. The options they choose generally reflect their current severity and future vulnerability (D. Maxwell, Caldwell, and Langworthy 2008; D. G. Maxwell 1996; D. Maxwell, Watkins, et al. 2003). By incorporating FSVI into the ABM, we are able to capture the dynamics and interactions occurring within and across the associated systems.

Although food security is defined in terms of food availability, access, utilization, and stability, its measurement is often limited to food production (availability) or access. In this study, we try to capture all four dimensions for measuring food security in our analysis. We evaluate food availability and access through analyzing household food production, social interactions, and resource availability. Similarly, we measure utilization using household calorie sufficiency. The simulations we perform provide information on the temporal stability of household food security.

This dissertation is organized into three papers, each with specified research questions. The first paper delves into household food systems in Koutiala. The second paper explores the trajectories of household food security under climate change and population growth, and the third paper evaluates selected policy intervention. The following research questions guide this study:

Research Question 1: What are the actors and factors of household food security? How do household actions and interactions affect their food security?

Research Question 2: How do dynamic interactions across socio-economic, climatic, and bio-physical systems spatially and temporally affect household vulnerabilities to food insecurity?

Research Question 3: What are the global and local level management recommendations for effective policy interventions?

The development of ABM needs information on agents, their properties, actions, and interactions. In Paper one, we use qualitative field narratives to identify the actors (agents) of food security, their attributes, and actions/interactions responsible for maintaining food security at the households in Koutiala. Qualitative data, primarily narratives, is an excellent source of information. The narratives contain rich contextual information for systems representation essential for model development. However, qualitative data processing and extraction is complex, and time and resource consuming. ABM developers often avoid extracting model components from qualitative data. Models are usually developed ad-hoc, based on modelers' subjective interpretation of target systems. The resulting models often have questionable quality and reliability. In this paper, we use Natural Language Processing tools to extract ABM components from qualitative narratives. The process is largely unsupervised and, therefore, highly efficient. Further, it limits manual manipulation, reducing opportunities for human bias introduction during model development.

In paper two, we integrate a biophysical crop model with an ABM of household food systems to analyze household vulnerability to food insecurity. We simulate a 'business-as-usual' scenario based on the current level of farm management, population growth, and expected climate change. The ABM receives information on household crop production from the crop model. Household food sufficiency is determined by calculating food availability and demand at the household level. The model treats food sufficient households as food secure. Food insufficient households look for coping alternatives, and the ABM provides FSVI indices to the households based on the severity indicated by alternatives used by the households.

In paper three, we evaluate the effects of global and local level policy interventions on household food security in the study area. We simulate alternative futures combining different farm management, population growth, and climate change interventions. We explore the trajectories of household food security under combinations of interventions. Additionally, we compare the outputs with the 'business-as-usual' scenario from paper two to assess the effectiveness of the interventions.

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CHAPTER 2

A LARGELY UNSUPERVISED DOMAIN-INDEPENDENT QUALITATIVE DATA EXTRACTION APPROACH FOR EMPIRICAL AGENT-BASED MODEL DEVELOPMENT.

Agent-based model (ABM) development needs information on system components and interactions. Qualitative narratives contain contextually rich system information immensely useful for ABM conceptualization. However, traditional qualitative data extraction is usually manual, complex, and time and resource consuming. As a result, modelers often shy away from using qualitative data or follow unorthodox ad-hoc approaches for ABM development. That could yield models difficult to validate and replicate. Besides, manual data extraction is generally bias-prone and may produce models of questionable quality and reliability. In this study, we present a largely-unsupervised qualitative data extraction for ABM development. Using a combination of semantic and syntactic Natural Language Processing tools, our methodology extracts information on system agents, their attributes, and actions and interactions. In addition to expediting information extraction for ABM, the largely-unsupervised approach also minimizes biases arising from modelers' preconceptions about target systems. To make it usable on large unstructured datasets, we also introduce multiple automatic and manual noise-reduction stages. We demonstrate the approach by developing a conceptual ABM of household food security in rural Mali. The data for the model contains a large set of unstructured qualitative field narratives. The data extraction is swift and mainly automatic and devoid of human manipulation. We contextualize the model manually using the extracted information. For added credibility and validity, we also put the conceptual model to stakeholder evaluation.

2.1 Introduction

Qualitative data provides thick contextual information (Miles 1979; Rich and Ginsburg 1999; Watkins 2012) that can support reliable quantitative socioecological systems (SES) model development. Qualitative data analysis explores systems components, their complex relationships and behavior (Kemp-Benedict 2004; Rich and Ginsburg 1999; Watkins 2012), and provides a structured framework that can guide the formulation of quantitative SES models (Ackermann, Eden, and Williams 1997; Coyle 2000; Forbus and Falkenhainer 1990; Wolstenholme 1999). However, qualitative research is complex, time, and resource-consuming (Miles 1979; Watkins 2012). Data analysis usually involves keyword-based data extraction and evaluation that requires multiple coders to reduce biases. Moreover, model development using qualitative data requires multiple, lengthy, and expensive interactions with stakeholders (Polhill, Sutherland, and Gotts 2010), which adds to its inconvenience. Consequently, quantitative modelers often shy away from using qualitative data for their model development. Often, modelers either entirely skip qualitative data analysis or use unorthodox approaches for framework development. This usually fails to capture the complex dynamics of target systems and produces inaccurate and unreliable outputs (Landrum and Garza 2015).

The development in the information technology sector has substantially increased access to qualitative data over the past few decades. Harvesting large, credible data is crucial for reliable model development. Increased access to voluminous data presents a challenge, as well as an opportunity for model developers (B. Runck 2018). However, qualitative data analysis has always been a hard nut to crack for SES modelers. Most of the existing qualitative data analyses are highly supervised (i.e., done mainly by humans) and, hence, bias-prone and inefficient for large datasets. An approach that can efficiently analyze and extract qualitative data for developing credible, reliable and valid SES models is urgently required. This study presents a methodology that uses an efficient largely unsupervised qualitative data extraction method for credible Agent-based Model (ABM) development using Natural Language Processing (NLP) toolkits. As the process of information extraction is unsupervised and does not require manual interventions, it reduces potential for subjectivity and biases in the model development. ABM, one of the widely used SES models, requires information on socioecological agents, their attributes, and interactions for its development.

The paper is organized as follows. Section 2.2 describes the importance of qualitative data and outlines some of the existing approaches for translating qualitative data to empirical ABM. In section 2.3, we present a largely unsupervised domain-independent qualitative data processing and extraction using NLP for ABM development. We use the approach to develope an ABM of household food security in Koutiala Mali, which is reported in section 2.4. Section 2.5 outlines some of the limitations and recommendations for future research. Finally, Section 2.6 concludes our paper.

2.2 Background

ABM is useful for understanding phenomena that emerge from nonlinear interactions of autonomous and heterogeneous constituents of socioecological systems (An et al. 2005). ABM is a bottom-up approach; interactions occurring at micro-level produce complex and emergent phenomena at a macro (higher) level. To simulate such behaviors, ABM requires micro-scale data. However, obtaining data at the required scale is not always feasible. ABM had enjoyed a prosperous era of nonempirical models that showcased the model's effectiveness in exploring complex systems (Janssen and Ostrom 2006). Using synthetic data, the nonempirical abstract models simulate simple system behaviors to generate and test complex systems theories (O'Sullivan et al. 2016). Models like Conway's Game of Life and Shelling's Segregation are some of the first and renowned nonempirical ABMs, that despite lacking real-world data, simulate simple behaviors to adequately explain system complexity and emergence (Axelrod 1997).

As the access to micro-level data becomes easier, modelers are increasingly using empirical data for more realistic system representation and simulation (Janssen and Ostrom 2006; O'Sullivan et al. 2016; Robinson et al. 2007). These empirical models use quantitative as well as qualitative data to evaluate systems theories. Quantitative data is primarily useful for parameterizing and running simulation. Additionally, quantitative model outputs are also used for model verification and validation. Qualitative data, on the other hand, finds its uses at various stages of the model cycle (Seidl 2014). Apart from the routine tasks of identifying systems constituents and behaviors for model development, qualitative data also supports the model structure and output representations

(Grimm, U. Berger, et al. 2010; Ligmann-Zielinska, Siebers, et al. 2020; B. Müller et al. 2014). Qualitative model representations facilitate communication for learning and model evaluation and replication.

Several researchers believe that the qualitative/quantitative dichotomy is artificial and inaccurate (Gorard 2002; Kemp-Benedict 2004; Rich and Ginsburg 1999). They argue that both approaches have similar philosophies - both aim to advance scientific knowledge through verified tools and methods. Scientific rigor and integrity of theoretical knowledge are central to both paradigms (Gorard 2002; Rich and Ginsburg 1999). Although their inductive and deductive approaches are different, data used for the analyses are predominantly nonbinary. Numbers can be textualized, and textual data can be counted (Gorard 2002). However, pro-qualitative researchers challenge such ideas. They believe that the qualitative and quantitative approaches have distinct philosophies, characteristics, and goals (Leininger 1992). They find quantitative research to be highly rigid and context-deprived (Rich and Ginsburg 1999; Watkins 2012). On the contrary, the quantitative domain finds qualitative research vague, bias-prone, and without scientific rigor (Gorard 2002).

Such finger-pointing and blame game is omnipresent in the scientific community, especially in the post-Kuhn era (Niglas 2000). Moreover, there is a broader dissatisfaction amongst qualitative researchers as quantitative research is deemed more important in the scientific community and is prioritized for funding and publication. Improperly mixed methods create more issues than they typically address (Leininger 1992). However, SES models can naturally embrace both approaches. ABM, specifically, uses both deductive and inductive approaches to generate and test systems theories. Epstein (2006) promotes such ABM quality as a generative social science, while Axelrod (1997) calls it a third way of doing science.

Mixed-methods are gradually getting traction in the wider modeling community (Forbus and Falkenhainer 1990; Gorard 2002; Kemp-Benedict 2004; J. D. A. Millington and Wainwright 2016; Wolstenholme 1999). Specifically, qualitative analysis is used at the beginning of research to explore system dynamics that inform the development of structured frameworks for quantitative model formulation (Coyle 2000; Forbus and Falkenhainer 1990). Without such frameworks, quantitative modelers often get bogged down by systems complexities. Besides, qualitative research also lays down model assumptions explicitly that solidify the credibility and reliability of the resulting models (Ackermann, Eden, and Williams 1997; Coyle 2000; Forbus and Falkenhainer 1990; Wolstenholme 1999). As a result, such frameworks are frequent in the quantitative models across various disciplines including engineering (Forbus and Falkenhainer 1990), transportation management (Ackermann, Eden, and Williams 1997), public health (Rich and Ginsburg 1999), geography (Ligmann-Zielinska and Jankowski 2010), and other socioecological systems (Schmitt Olabisi et al. 2010).

Some quantitative models have predefined structures for model development. System Dynamics, for instance, uses Causal Loop Diagrams as qualitative tools (A. Ford and F. A. Ford 1999). Causal Loop Diagrams elucidate systems components, their interrelationships, and feedbacks that can be used for learning and developing quantitative System Dynamics models. ABM, however, does not have a predefined structure for model development; models are mostly based on ad-hoc structures. Structural validation is crucial for ABM (Heath, Ciarallo, and Hill 2012). However, such ad-hoc development is problematic for model validation and replication (Grimm, Augusiak, et al. 2014). Besides, similar systems can have different structures that make learning through models extremely difficult (O'Sullivan et al. 2016). Hence, there is a need for a standard structure for the development of credible, reliable, and educational ABMs.

2.2.1 The use of qualitative data for ABM conceptualization

Social and cognitive theories often form the basis for translating qualitative data to empirical ABM (Becu et al. 2005). Since gathering and organizing micro-level qualitative data is difficult, using theories streamlines data management and analysis for model development. Theories like Belief-Desire-Intension (Balke and Gilbert 2014), Theory of Planned Behavior (Edwards-Jones 2006), Utility Maximization (Doscher et al. 2014), and Consumat (Janssen and Jager 1999) are typical for defining behavioral rules in ABM. Since social behavior is complex and challenging to comprehend, the use of social and cognition theories helps in determining the expected behavior of the system.

Another school of thought bases model development on stakeholder cognition. Rather than relying mainly on social theories, this approach focuses on extracting empirical information about system components and behaviors. Nicolas Becu et al. (2003) identified two approaches for using stakeholder information in model building – a modeling view and a transfer view. The modeling view requires direct involvement of stakeholders in model development. Participatory or companion modeling, as well as role-playing games, are some of the conventional approaches of eliciting stakeholder knowledge for model development (Robinson et al. 2007). Stakeholders usually develop model structures in real-time, while some modelers prefer to process stakeholder's information after the discussions. For instance, Bharwani (2006) employs computer technologies to post-process stakeholder responses to develop a rule-induction algorithm for her ABM. Stakeholders are assumed to be the experts of their systems, and using their knowledge in model building makes model valid and reliable. However, this approach also has its limitations. Working with stakeholders can be complicated and may require specialized skills. Stakeholder bias (Seidl 2014) is also a common problem. Relying entirely on stakeholders for model development, on the other hand, can completely hijack the initially intended model objectives. As social systems are 'socially constructed,' conflicting views on the systems are also likely to occur. Collating the conflicting and contrasting views in one representation may not always be possible. That may require developing multiple models of the same system to reflect different perspectives (Nicolas Becu et al. 2003). However, Participatory Modeling (Voinov and Bousquet 2010) has been continually developed to acknowledge and minimize various biases that may be introduced by stakeholders involvement in model building (Sterling et al. 2019; Voinov, Kolagani, et al. 2016).

Stakeholder involvement is not always feasible; for instance, when modeling remote or historical events. In such cases, a transfer view is preferred. The transfer view requires textual information, usually in the form of narratives or interviews. Modelers use knowledge engineers and information elicitation tools for information extraction. Thus, translating empirical textual data into agent architecture is difficult and requires concrete algorithms and structures (Seidl 2014). Edmonds

(2015) formulated a context, scope, and narrative element structure for eliciting model elements from textual data. Modelers first explore the context of the narratives and then identify potential context-specific scopes. Once context and scopes are identified, according to Edmonds (2015), identifying narrative elements becomes easy.

Many ABM modelers have formulated structures for organizing qualitative data for model development. For instance, Ghorbani, Schrauwen, and Dijkema (2013) used Ostrom's Institutional Analysis and Development (IAD) framework for managing qualitative data in their Modeling Agent-system based on Institutions Analysis (MAIA). MAIA comprises five structures: collective, constitutional, physical, operational, and evaluative. Information on agents is populated in collective structure while behavior rules and environment go in constitutional and physical structures, respectively. A similar example can also be found in Gilbert and Terna (2000). They presented an Environment-Rule-Agent structure for organizing qualitative data for ABM development. Likewise, the MameLuke framework developed by Huigen (2004) is also a highly popular approach. It uses Action-in-Context (De Groot 1992) for translating real-life stories into computerized ABM.

2.2.2 Formulating ABM for model development

ABMs are essentially computer tools that have software agents and environments. The high-level model descriptions elicited from qualitative data needs to be translated to low-level computer languages. Frequently, modelers are not computer programmers. That often prompts modelers to represent their models to programmers. The widely used ABM representations are either in the form of natural languages (e.g., ODD (Grimm, Railsback, et al. 2020)), Graphics (e.g., UML (Bersini 2012)), or formal language (e.g., pseudocodes, ontologies). B. Müller et al. (2014) compared these approaches and found that UML representation has broader applicability in coding, validating, communicating, and replicating models. UML is a standardized graphical representation of software development (Bersini 2012). It has a set of well-defined class and activity diagrams that are effective in representing the inner workings of ABMs (Collins et al. 2015). Although there are other forms of graphical ABM representations like Petri Nets (Bakam et al. 2000), Conceptual

Model for Simulation (Heath, Ciarallo, and Hill 2012) and sequence and activity diagrams (Gilbert 2004), UML is natural in representing ABM. Due to which, Miller and Page (2009) expected UML to be the default lingua franca of ABM. Recently, ABMs are increasingly being represented using UML (Li et al. 2015; Serrano and Iglesias 2016). Furthermore, ABM specific UMLs like Agent UML (AUML) (Bauer, J. P. Müller, and Odell 2001) that captures the adaptive nature of agents and Agent Modeling Language (AML) (Trencansky and Cervenka 2005) are also being developed (Subburaj and Urban 2018).

ABM has a close resemblance to Object-Oriented Programming (OOP) (An 2012; Dearden and Wilson 2012; Gilbert 2004; Simoes 2012). In OOP, objects belong to classes; they have attributes as well as methods and relationships. Likewise, in ABM, agents have attributes and actions/interactions. Code proficient modelers often develop their ABMs using object-oriented programs (T. Berger 2001; Standish 2008). OOP flows naturally and is easy to understand (Bersini 2012; Torrens 2010); hence, translating ABM to OOP makes coding much easier (Crooks and Heppenstall 2012). However, ABM is not necessarily an OOP. Many ABMs have been developed using non-OOP NetLogo (Krejci et al. 2016; J. D. Millington 2012). NetLogo effectively caters to modelers who have an elementary coding experience (Tisue and Wilensky 2004).

UML is widely accepted for representing OOP (Bauer, J. P. Müller, and Odell 2001). Transferring narratives to an object-oriented framework and representing it through UML is useful for communicating and developing ABM. Many software engineers are exploring ways to extract information from qualitative data directly to object-oriented frameworks. Similarly, database designers are also trying to auto-populate entity-relationship diagrams from textual information (Harmain and Gaizauskas 2000). They primarily exploit the syntactic structure of sentences for information extraction. The syntactic analysis usually treats the subject of a sentence as a class (an entity for a database) and the main verb as a method (relationship for a database).

Software engineers have been exploring various supervised and unsupervised approaches for information extraction. In supervised approaches, syntactical patterns are defined (Clark et al. 2012), and text is manually scanned for such patterns. In unsupervised information extraction, the machine does the pattern matching. NLP (Loper and Bird 2002; Manning, Surdeanu, et al. 2014) toolkits are increasingly used for unsupervised pattern matching and information extraction (Fraga et al. 2017; Salloum et al. 2018). Tools like lemmatizing, tokenizing, stemming, and part of speech tagging (Bird, Klein, and Loper 2009) are useful for syntactic information extraction. These tools can normalize texts and identify subjects and main verbs from their sentences.

Supervised approaches are reliable but slow. On the contrary, the faster unsupervised approaches are difficult and prone to errors, mostly due to the word sense ambiguation (Al-Safadi 2009). A purely syntactical analysis cannot capture the nuanced meaning of texts, which is often the culprit of the problem. Recently, pattern matching also involves semantic analysis. External databases of hierarchically-structured words (e.g., WordNet, VerbNet) (Navigli 2009), as well as machine learning tools, are increasingly used for understanding semantics for reduced word sense ambiguity (Husain and Khanum 2016; Orkphol and Yang 2019).

2.3 Using NLP for largely unsupervised ABM development

NLP is instrumental in efficiently analyzing, tagging, and extracting information from broad textual data (Liddy 2001; Sun, Luo, and Chen 2017). The ability to convert highly unstructured texts to structured information through predominantly unsupervised approaches is one of the main advantages of NLP in qualitative data analysis. NLP efficiently analyzes intertextual relationships using syntactic and semantics algorithms. Approaches like word co-occurrence statistics and sentiment analysis (Nasukawa and Yi 2003) are highly useful for domain modeling (Clark et al. 2012), and for exploring contextual and behavioral information from textual data. Similarly, its efficiency in pattern matching for information extraction is particularly important for model development. Although being present for decades in object-oriented programming and database development (Harris 1978; Lees 1970), NLP has a minimal footprint in ABM development.

The introduction of NLP in ABM development is very recent. Runk (B. Runck 2018; B. C. Runck et al. 2019) used NLP to model human cognition through web embedding. Word embeddings are contextually analyzed vector representations of texts. They place closely related texts next to each other. Placing agents with similar worldviews together supports theorizing agent decision-making. Although the approach helps in developing agent decision-making, it is not yet well equipped for developing a comprehensive agent architecture.

Padilla, Shuttleworth, and O'Brien (2019) applied NLP in conjunction with machine learning to create an ABM structure from unstructured textual data. Texts are translated to the agent-attribute-rule framework. They defined agents as nouns (e.g., person, place) that perform some actions, and attributes as words that represent some variables. Similarly, the sentences that contain agents or attributes together with action verbs are considered rules. The primary goal of their approach is to create an ABM structure mainly for communicating the model to non-modelers.

As with machine learning approaches in general, the Padilla el al. approach requires a large amount of training data. They used ten highly concise formally written ABM descriptions from published journals as their training datasets. Another limitation, according to the researchers, is the lack of precise distinctions between agents and attributes - attributes could also be nouns that might confuse the machine. Using repeated training with large data is found to be effective in increasing the accuracy of the agent-attribute-rule detection. However, the model frequently resulted in under and over predictions.

Our study proposes and tests a largely unsupervised domain-independent approach for developing ABM structures from unstructured, informal narratives using Python-based semantic and syntactic NLP tools Figure 2.1. The method primarily uses syntactic NLP approaches for information extraction directly to the widely accepted OOP framework (i.e., agents, attributes, actions/interactions), and creates UML for its representation. Since the approach is not based on machine learning, it does not require large training data. The semantic analysis is limited to the use of external static datasets like WordNet (https://wordnet.princeton.edu/) and VerbNet (https://verbs.colorado.edu/verbnet/). The process is mainly unsupervised and involves the following:

- Unsupervised data processing and extraction

- Data preprocessing (cleaning and normalization)
- Data volume reduction
- Tagging and information extraction

- Supervised contextualization and evaluation
    - UML/Model conceptualization
    - Model evaluation

2.3.1 Unsupervised data processing and extraction

2.3.1.1 Data preprocessing (cleaning and normalization)

Qualitative data analysis is computationally expensive. Unstructured narratives often contain redundant or inflected texts that can bog down NLP analysis. Hence, removing non-informative contents from large textual data is highly recommended at the start of the analysis. NLP is well equipped with stop words removal tools that can effectively remove redundant texts. Similarly, tools like stemming and lemmatizing are useful for normalizing texts to their base forms (Manning, Raghavan, and Schütze 2010).

2.3.1.2 Data volume reduction

Data volume reduction can tremendously speed up NLP analyses. Traditional volume reduction approaches usually contain highly supervised keyword-based methods. Data analysts use predefined keywords to select and extract sentences perceived to be relevant (Namey et al. 2008). Keyword identification generally requires a priori knowledge on the system and is often bias-prone. We recommend a domain-independent unsupervised Term Frequency Inverse Document Frequency (TFIDF) approach (Ramos 2003) that eliminates the requirement for manual keyword identification. The approach provides weightage to individual words based on their uniqueness and machine-perceived importance. The TFIDF differentiates between important words and common words by comparing their frequency in individual documents and across the entire body of texts. Sentences that have high cumulative TFIDF scores are perceived to have higher importance. Given a document collection D, a word w, and an individual document d ϵ D, TFIDF can be defined as,

$f_{w,_d} * log(|D| \backslash f_w, D)$

where fw, d equals the number of times w appears in d, |D| is the size of the corpus, and fw, D equals the number of documents in which w appears in D (Ramos 2003).

2.3.1.3 Tagging and Information Extraction

Once the preprocessed data is reduced, tagging for agents, attributes, and actions/interactions can occur. We propose the following approaches for tagging agent architecture:

Candidate agents: Following the conventional approaches in database design and object-oriented programming, we propose the subjects of sentences to be identified as candidate agents. For instance, *the farmer* in '**The farmer** grows cotton' can be a candidate agent. NLP has well-developed tools like part-of-speech tagger and named-entity tagger that can be used to detect subjects of sentences.

Candidate actions: The main verbs of sentences can become candidate actions. The main verbs need to have candidate agents as the subject of the sentences. In the sentence 'The farmer **grows** cotton,' *the farmer* is a candidate agent and the subject of the sentence; *grows* is the main verb and, hence, a candidate action.

Candidate attributes: Attributes are properties inherent to the agents. Sentences containing candidate agents as subjects and *be* or *have* verbs as their primary (non-auxiliary) verbs provide attribute information. E.g. The farmer *is* **a member of a cooperative**. The farmer *has* **10 ha of land**. Additionally, the use of possessive words also indicates attributes. E.g., the cow in the sentence 'My **cow** is very small' is an attribute of 'I'.

Candidate interactions: Main verbs indicating relationships between two candidate agents are identified as interactions. Hence the sentences containing two or more candidate agents provide information on interactions. E.g., *The Government* **trains** the *farmers*.

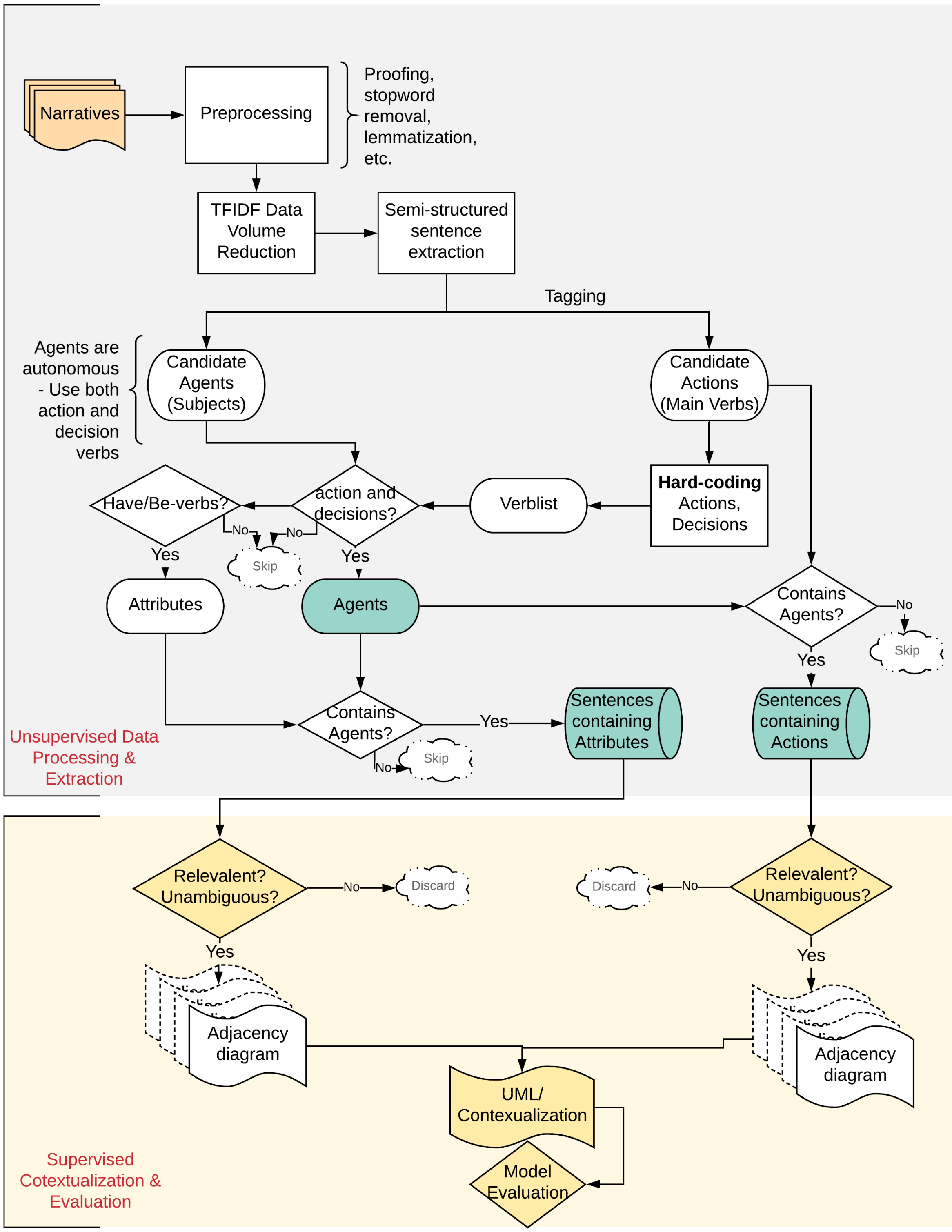

Figure 2.1: Largely unsupervised information extraction for ABM development, TFIDF: Term Frequency Inverse Document Frequency

Since the data tagging is strictly unsupervised, false positives are likely to occur. The algorithm can overpredict agents, as the subjects of all the sentences are treated as candidate agents. In ABM, however, agents are defined as autonomous actors – they act and make decisions. We propose to use a hard-coded list of action (e.g., eat, grow, walk) and decision (e.g., choose, decide, think) verbs to filter agents from the list of candidate agents. Only the candidate agents that use both types of verbs qualify as agents. Candidate agents that do not use both verbs are categorized as entities that may be subjected to manual evaluation. Similarly, people use different terminologies that are semantically similar. We recommend using external databases like WordNet to group semantically similar terminologies.

2.3.2 Supervised contextualization and evaluation

The unsupervised analysis reduces data volume and translates unstructured narratives to the agent-action-attribute structure. However, since the process is unsupervised, noise can still percolate to the outputs. Additionally, the outputs need to be contextualized. We suggest performing a series of supervised output filtration, followed by manual contextualization and validation.

The domain-independent unsupervised analysis extracts individual sentences that can sometimes be ambiguous or domain irrelevant. Hence the output should be filtered based on the level of ambiguity and domain relevancy. Once output filtration is done, contextual structures can be developed and validated with domain experts and stakeholders.

2.4 Development and evaluation of ABM of household food security using the proposed framework

We applied the above approach to develop a structural ABM of household food security using unstructured field narratives. The data contains 42 semi-structured interviews collected from different members (young and old; male and female) of farm households in Koutiala, Southern Mali. The interviews were initially conducted for developing mental models of household food security in the region (Rivers III et al. 2017), see, for example, Figure 2.2. The mental model development

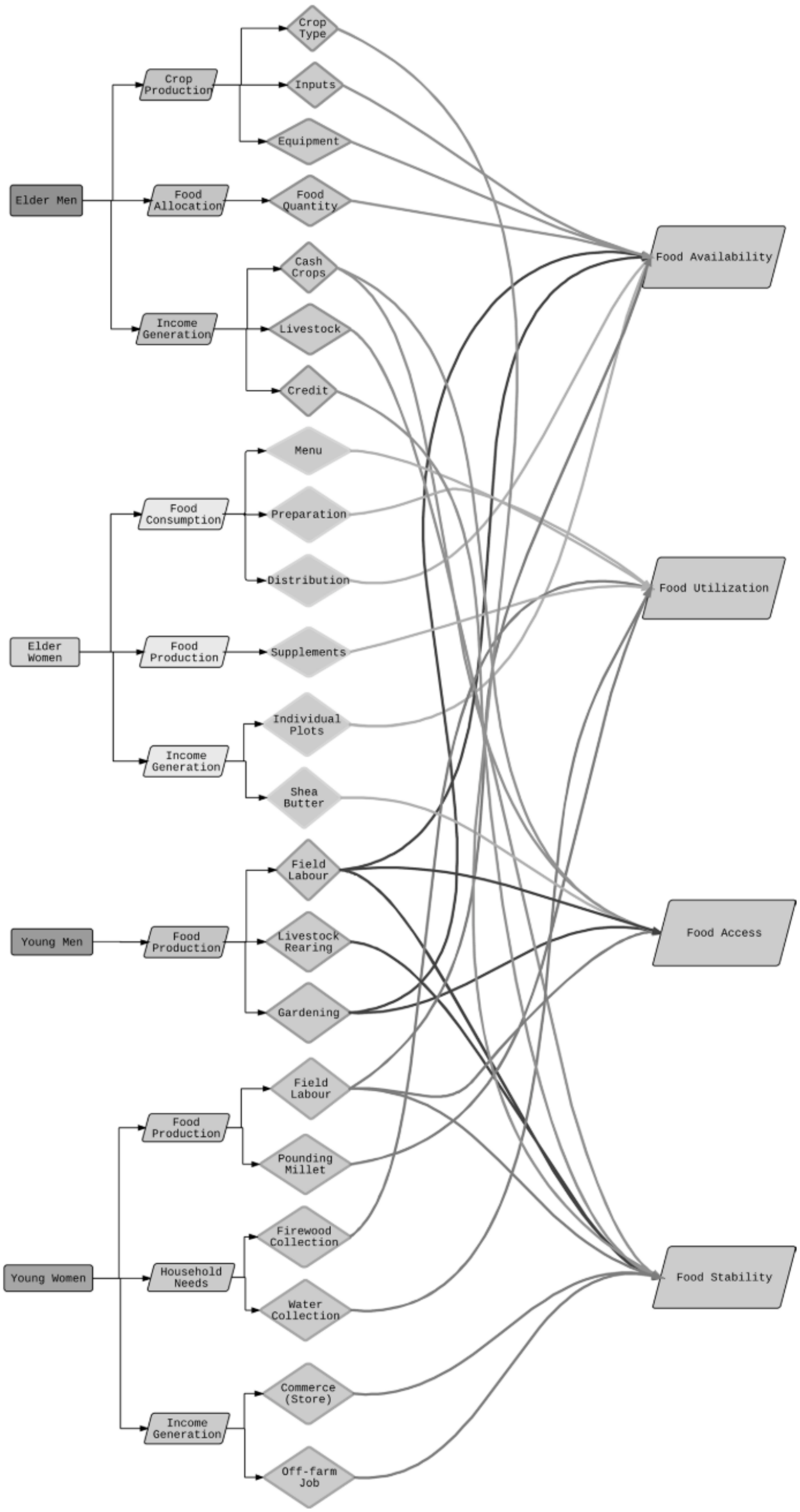

Figure 2.2: Mental Model of household food security (Rivers III et al. 2017)

Table 2.1: An excerpt of action and decision verbs

Decision Verbs	**Action Verbs**
adhere	abandon
advise	accelerate
approve	accept
assess	access
choose	accompany
comply	accord
consult	achieve
decide	acquaint
determine	acquire
discourage	add
educate	address
encourage	adjust
expect	adopt
favor	advertise
follow	affect
guide	afford
instruct	agree
learn	aim
obey	alert
oblige	allow
plan	analyze
prefer	apply
propose	appoint
provoke	appreciate
recommend	argue
refuse	arrange
regulate	arrive
reject	assemble
reprimand	assist
suggest	associate
withdraw	attach

```
candidate agents: {‘money’, ‘woman’, ‘water’, ‘porridge’, ‘household’, ‘father’, ‘i’, ‘food, ‘it’, ‘we’, ‘they’, ‘she’, ‘he’, ‘cereal’, ‘farm’}

agents: [‘i’, ‘it’, ‘we’, ‘they’, ‘she’]
```

Figure 2.3: Candidate agents before and after using the external database

followed the lengthy conventional qualitative data analysis approach that used multiple coders and keyword-based sentence extraction. That inspired us to develop a more efficient alternative data processing and extraction approach for ABM development.

For this study, we used Python 3.7 programming language (https://www.python.org/) along with several NLP libraries (e.g., scikit-learn, nltk, spacy, textacy) to perform data reduction, tagging, extraction, and structuration. We grouped the narratives by the member types (i.e., elder male, younger male, elder female, and younger female) and analyzed the grouped narratives collectively. After preprocessing the narratives using NLTK tools, we used the scikit-learn TfidfVectorizer to reduce the volume of qualitative data. Textacy was primarily used for identifying candidate agents, actions, and attributes. Additionally, Textacy extract (textacy.extract.semistructured_statements) was useful in converting sentences to structured outputs. We manually filtered the unsupervised outputs based on their domain relevancy and ambiguity. The final outputs were then visualized and conceptualized using Gephi (https://gephi.org/) and Lucid Chart (https://www.lucidchart.com/) platforms.

As expected, the unsupervised tagging overpredicted the agents. Subjects that do not make a decision were also identified as candidate agents. We created an external database of action/decision verbs (Table 2.1) that somewhat addressed the problem. There was more than a 60% reduction in the number of agents after the external database was used (e.g., Figure 2.3). The initially identified candidates, such as porridge, food, cereal, or farm, were discarded by the filtration process. We also used external WordNet database to group semantically similar actions.

Next, we developed UML class diagrams (Figure 2.4) and contextual diagram (Figure 2.5) using the extracted information. We found that different members of households support household food security differently (see Appendix A; Appendix B). Male members of the households are generally

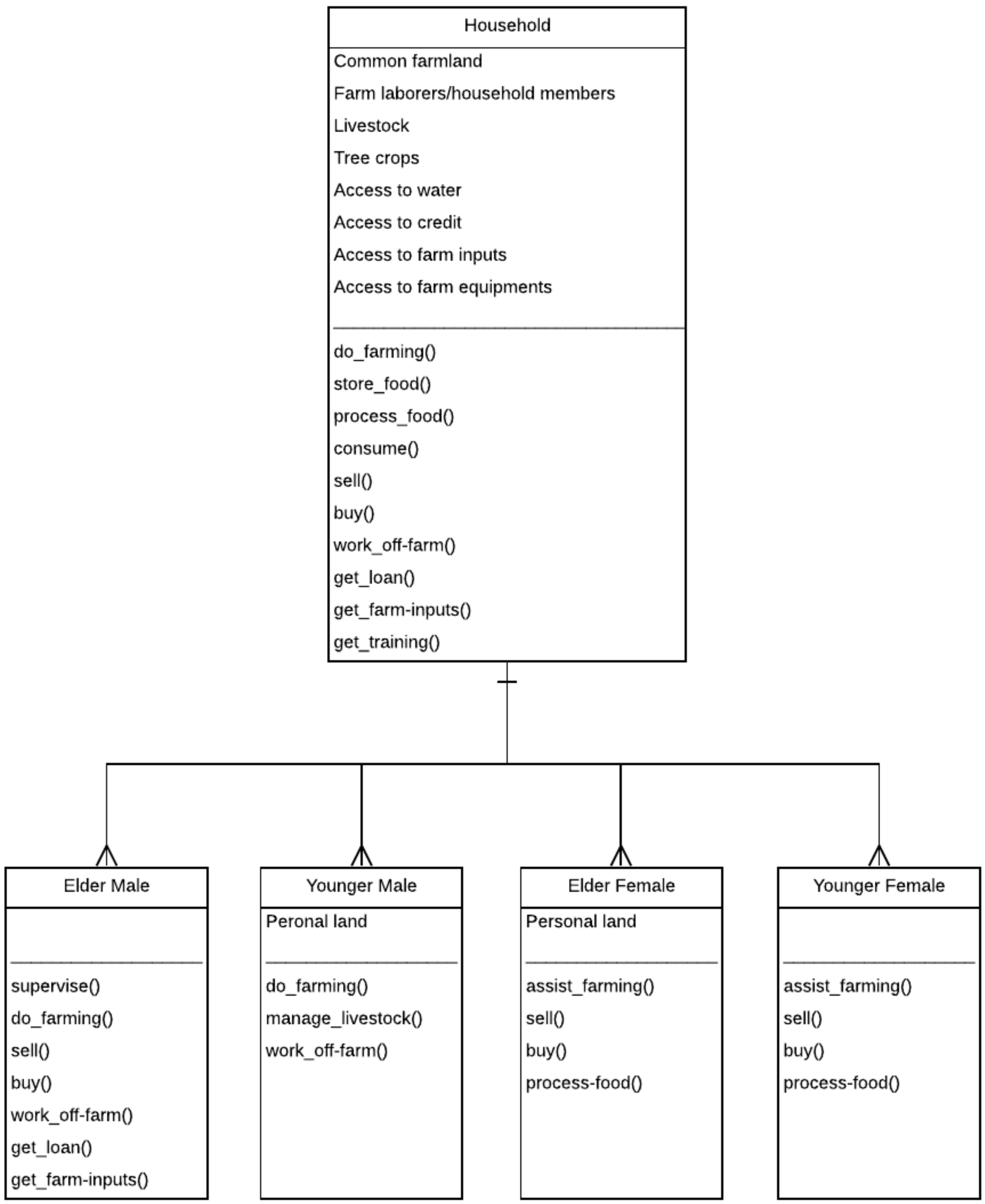

Figure 2.4: UML class diagram of agents of household food security

involved in farming. They grow cereal crops, vegetables and are also into cash-cropping. Women look after household works and also support men in the farm. Households generally consume the food they produce. In case of food shortages, households seek help from their fellow villagers or buy food from the market. They use money obtained from cash-cropping for buying food. Additionally, women in the households are involved in small businesses that can support food purchases. Some households may need to rely on off-farm jobs or sell their livestock to buy food. There are also other organizations and credit agencies that provide the households with credits and supports.

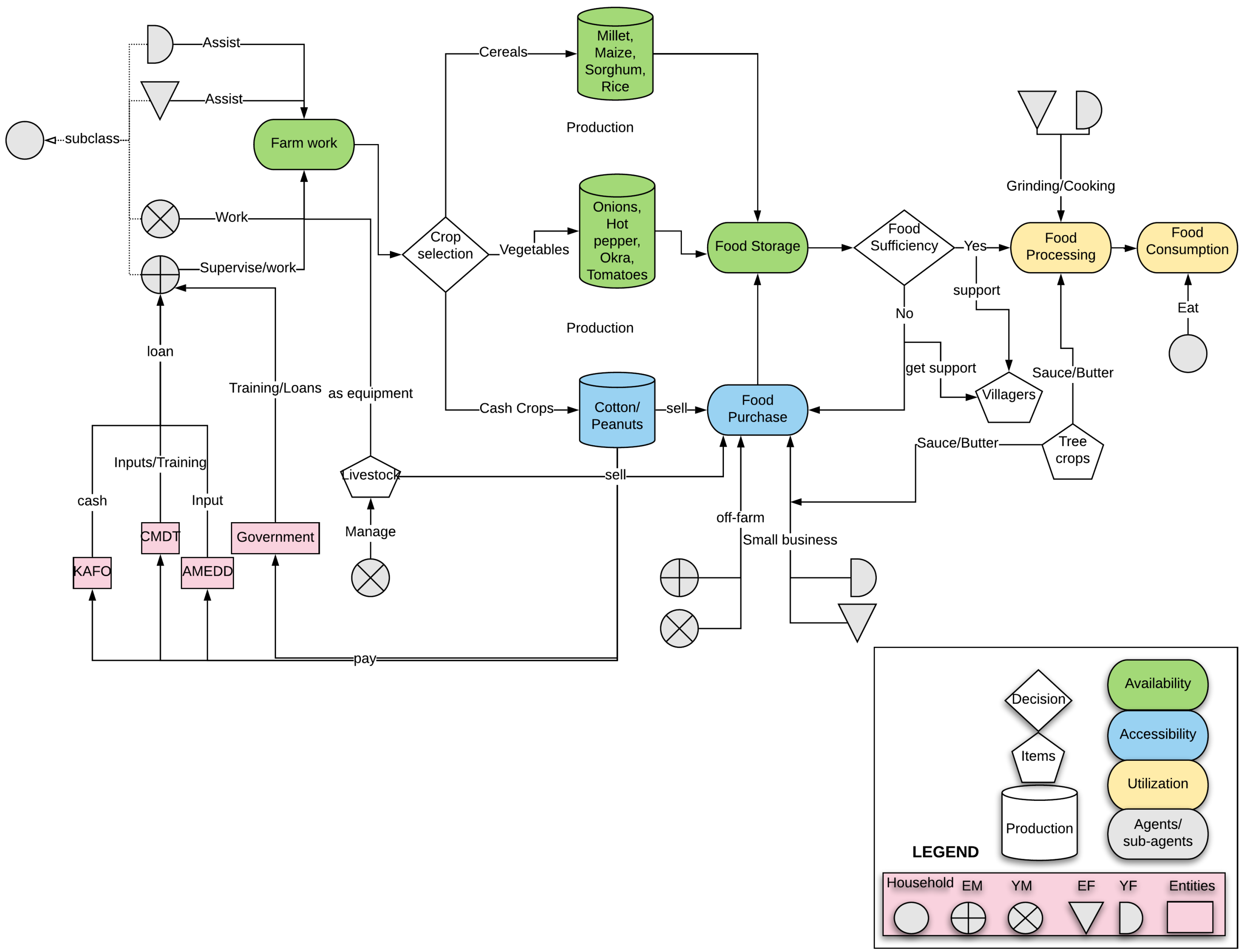

Figure 2.5: Conceptual model of household food security in Koutiala, Mali (EM: Elderly male, YM: Younger male, EF: Elderly female, YF: Younger female)

We simplified the contextual model (see Appendix D) and brought it to the stakeholders (interviewees) for validation. The stakeholders received the structure well and acknowledged that it included all the principal dynamics of the household food system. They, however, pointed out that the contextualized structure did not provide the dynamics of the government and non-government actors. Since the input data only contained interviews from farm households, we failed to capture the dynamics occurring outside of the households. In addition to representing the dynamics of the household food system, the structure also revealed data gaps. More information needs to be gathered on the government and non-government actors of household food security.

2.5 Limitations and future direction

The proposed unsupervised information extraction picked individual sentences based on their cumulative TFIDF weights. Some of the individually extracted sentences lacked contextuality and were ambiguous. To add context and reduce this ambiguity, we propose to use neighboring sentences at the unsupervised data extraction and processing phase (Figure 2.1). We hypothesize that extracting a tuple of preceding and trailing sentences along with the identified sentence, could provide vital contextual information. Similarly, some of the extracted sentences contained pronouns. Without the information on preceding sentences, these pronouns were impossible to resolve. Extracting the preceding sentence should help in resolving their references. NLP also has a coreference resolution tool that automatically replaces pronouns with their referenced nouns. However, the tool is still in development. We found that it generated too many errors that would require manual checks. We had to proceed without using the tool, and the pronouns identified as agents were ignored.

We only collected information on agents, attributes, and actions/interactions for ABM. However, ABM also requires information on agent decision-making. Although the use of social and behavioral theories in defining agent decision-making is predominant, empirically derived decision-making frameworks are context-specific and, therefore, more desirable. We realize that some sentences are particularly useful in deriving agent decision-making. Specifically, the conditional sentences like ‘if it rains, we plant maize,' and compound sentences like 'when production is low, we buy food from the market' can reveal decision-making. Harvesting these sentences with semantics and machine learning approaches can open up new avenues for formulating empirically-based decision-making rules for ABM.

Information obtained in the outputs is limited by the information contained in the input. We noticed that agent tagging, after using the action and decision verbs, underpredicted agents. Entities like 'father' and 'the government' should also be identified as agents of this particular system. However, since subjects did not use both types of verbs (action and decision) in the provided narratives, some information was missed out. Additionally, stakeholders pointed out that our model structure did not include the dynamics of the governmental and non-governmental actors. It prompts a need for a careful analysis of entities that failed to qualify as agents for data gaps. Furthermore, the narratives (see Appendix C)went through different stages of translations (from local dialect to French and English) that could have corrupted some of their original meanings.

2.6 Conclusion

Complexities, ambiguities, and difficulties in data processing often discourage ABM developers from using qualitative data for model development. This prevents modelers from using rich-contextual information about their target systems. ABMs are usually developed using ad-hoc approaches, potentially producing models that lack credibility and reliability. In this paper, we introduced a systematical approach for ABM development from unstructured qualitative narratives using NLP. The proposed methodology contained largely unsupervised, domain-independent, efficient, and bias-controlled data processing and extraction for ABM. We demonstrated its effectiveness by developing an ABM of household food security from large open-ended qualitative field narratives. Additionally, we outlined some of the significant limitations of the approach and recommended improvements for future development.

We initially aimed to develop an efficient and bias-free, completely unsupervised information extraction for conceptualizing an ABM. After preliminary algorithm development, we realized that, with the current level of NLP capabilities, entirely unsupervised data processing and conceptualization is not realistic. We decided to use manual filtration and contextualization that potentially introduced subjectivity and biases in model development. To address this deficiency, we performed a stakeholder validation to check for subjectivity and biases.

Although we could not fully develop a completely unsupervised approach, we successfully managed to reduce subjectivity and biases through limiting manipulation in data extraction. Data processing and extraction are fully unsupervised, and manual inputs are only required towards the end of model development. That effectively limits the opportunities for introducing human bias in model development. Furthermore, the unsupervised approach is much faster compared to manual coding. The NLP development community is highly active, and hopefully, these limitations will soon be resolved, making semantic and syntactic NLP more effective for unsupervised information extraction and model conceptualization.

APPENDICES

APPENDIX A

HOUSEHOLD-LEVEL ACTION AS DESCRIBED BY ELDERLY MALES

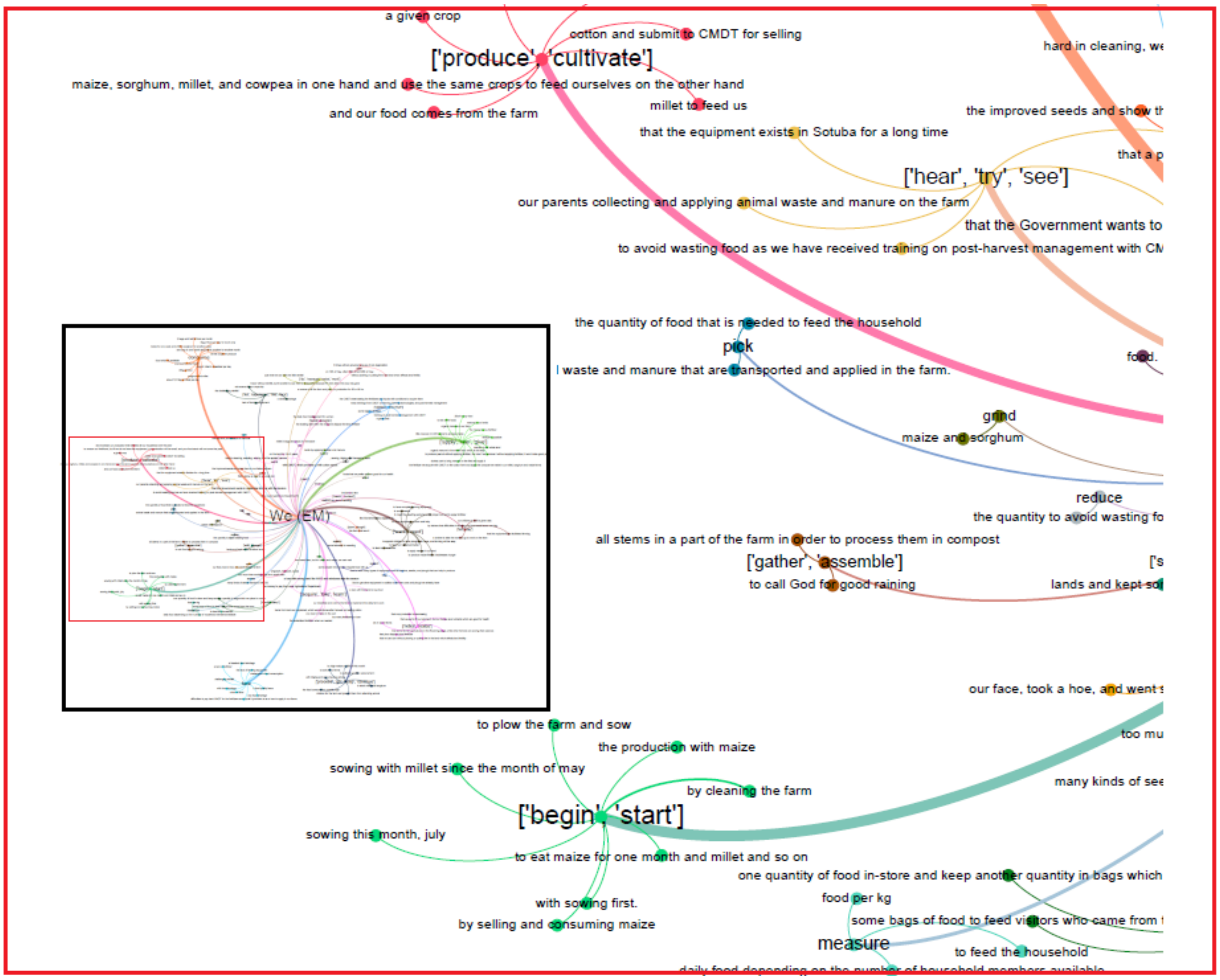

Figure A.1: Household-level action as described by elderly males

APPENDIX B

INDIVIDUAL ACTIONS AS DESCRIBED BY ELDERLY MALES

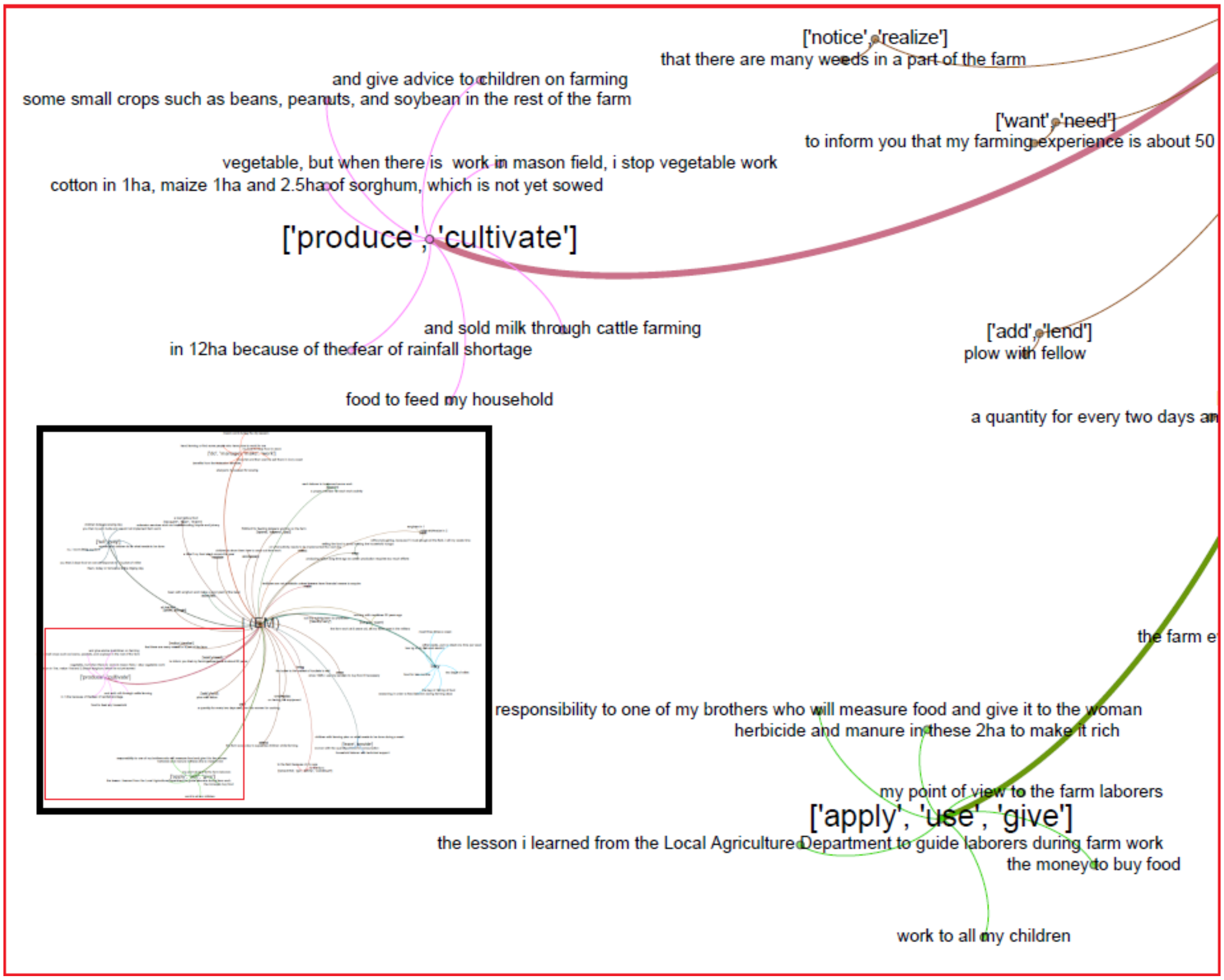

Figure B.1: Individual actions as described by elderly males

APPENDIX C

AN EXCERPT FROM THE FIELD NARRATIVES

Enumerator: When the production reaches home, how do you consume it?

Surveyed: First of all, we are 48 people in my household. After harvesting, we beat and weigh the crops. Then, we pick the quantity of food that is needed to feed the household. That quantity is given to women for cooking. We continue with that quantity until the new crop is harvested. When food is cooked and ready for eating, it is distributed by a plate to five and six persons who eat together. As the daily food consumption is known, we know what quantity we can sell to address household needs. You know, when crops are harvested, we tie them. Then we pick some pieces for beating. After beating, we weigh and stock. Then, we know the existing quantity in the store. If it is maize, for example, we have a cart and beating machine. We take one load of maize in the cart. Then we beat and weigh it and finally stock in the store. Farmers start beating crops and stock them. Because, a researcher like you, **IER** of **Sikasso** and **CMDT** trained us on post-harvest management. By following lessons learned from training, our food won't be over. Even if it happens that our food finishes, we would know what food to buy without any difficulties. With lessons acquired, we can produce and increase our production that will feed all our household over the year. Unless our food is stolen, it will cover for the year.

Enumerator: What are the main crops you are producing?

Surveyed: We produce maize, sorghum, millet, and cowpea in one hand and use the same crops to feed ourselves on the other hand. Some farmers prefer feeding themselves with millet all over the year. Even if they produce maize, they sell it. Although other farmers prefer maize, we consume all the crops we produce. We may consume one crop in one month and shift to another for another month. This is how we shift food consumption.

Enumerator: Who decides to shift from one food to another?

Surveyed: It depends. Some crops are easier to process than others. So, when there is the farm, we decide to consume crop, which is easy and quick to process. But, only one person is responsible for picking the food for daily consumption.

Enumerator: How many kgs do pick per day for feeding the 48 people?

Surveyed: It depends. During the farm work, we consume about 12/13kg of millet per day. Sometimes it is 10 kg. As far as maize is concerned, we consume 16 kg per day. We grind maize and sorghum. Some people grind millet, but we do not grind millet. We also consume 6 kg of millet in breakfast per day. If we add the 6 to 12/13, it reaches 18/19 kg. Small children also eat too much, so we must keep the food consumption quantity high. As Chief of the village, we sometimes stock some bags of food to meet stranger feeding who came from the town. We often support some people who came to request food with us.

Figure C.1: An excerpt from the field narratives (Note: Conversation took place in a local dialect that was later transcribed into English by a local translator)

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CHAPTER 3

ANALYZING HOUSEHOLD VULNERABILITY TO FOOD INSECURITY IN RURAL SOUTHERN MALI - A COUPLED BIOPHYSICAL AND SOCIAL MODEL APPROACH.

Household food security is dependent on, among other things, food production and access. However, food security discourse is dominated by the productionist arguments, and the role of food access is often ignored. Food security lies at the interface of biophysical, climatic, and socioeconomic systems and requires a systems approach for evaluation. In this study, we integrate a biophysical crop model with an agent-based model (ABM) of household food systems to analyze household vulnerability to food insecurity in rural southern Mali. The crop model analyzes the effects of biophysical and climatic environments on household food production, while the ABM evaluates the effects of socioeconomic systems on household food access. We measure household vulnerability to food insecurity using a coping-based food security vulnerability Index (FSVI). The FSVI reflects households' current severity and also indicates their future vulnerability to food insecurity. Vulnerability to food insecurity results from complex and dynamic interactions between biophysical and social systems. By integrating the FSVI into the model, we capture the interplay between the dynamic systems for the vulnerability analysis. We simulate a 'business-as-usual' scenario and find that around 80% of the regional households are likely to be food insecure by 2050. Large families and those living in the North are more susceptible to future food insecurity. However, the severity of food insecurity is higher especially in some smaller families.

3.1 Introduction and Background

Despite realizing the importance of food access for decades (Sen 1981), food availability still dominates the food security discourse. Regional food availability is often used as a sole indicator of food security (Pinstrup-Andersen 2009), and policies are fixated on increasing food production. However, food security is a multicausal issue that varies across households. Multiple factors, including lack of resources, socio-cultural norms, and policies, often dictate households' access to available food. As food access is non-homogenous, regional food availability does not adequately reflect household food security. A comprehensive food security analysis, therefore, needs evaluating heterogeneous food availability and access at the household level.

In this study, we develop a spatial agent-based model (ABM) of a household food system coupled with a process-based crop model to analyze household vulnerability to food insecurity in rural Southern Mali. The crop model examines the effects of biophysical and climatic factors on household food production. At the same time, the ABM explores the influence of socioeconomic factors on adequacy and stability of household food access. Social vulnerability is often defined in terms of risk exposure, coping capacity, and recovery potential (Bohle, Downing, and Watts 1994; Watts and Bohle 1993). We define vulnerability at the interface of biophysical and socioeconomic systems and measure it using a coping-based food security vulnerability index (FSVI). The FSVI measures the current severity of food shortages at the households as well as provides an outlook on their future vulnerability.

Malian agriculture had a disappointing past; it could not seize the benefits of the Green Revolution (Otsuka and Muraoka 2017). The promoted technologies and farm management were largely inadequate for improved crop production (Djurfeldt et al. 2005). The regional farmers could not intensify their agriculture, and their productivity remained stagnant for decades (M. E. Brown, Hintermann, and Higgins 2009). On the other hand, due to rapid population growth, food demand kept on rising. Farmers had to rely on extensification to meet the expanding food demand. Also, due to poor management, there was widespread soil degradation (Ruelland, Levavasseur, and Tribotté 2010) that further deteriorated the agricultural productivity.

The outlook of Malian agriculture looks bleak. The country is expected to be profoundly impacted by future climate change. All of the General Circulation Models (GCMs) used by the Intergovernmental Panel for Climate Change (IPCC) predict a warmer Mali (Traore et al. 2013). Since crop yield generally declines with increased temperature (Bassu et al. 2014), Mali is likely to see reduced crop production under climate change. Some climate models foresee increased rainfall in the future (Patricola and Cook 2010; Sultan and Gaetani 2016) that can arguably benefit crop production. However, an increased frequency of erratic rainfall predicted under climate change, together with warmer weather, is expected to nullify such benefits (Sivakumar 1988).

The northern half of Mali lies in the Saharan region. It is highly arid and not suitable for agriculture. However, southern Mali receives higher rainfall and is more productive. Koutiala (Figure 1.2), our study area, lies in the Sudano-Guinean region in the South and receives 600-1400mm of annual rainfall (Falconnier et al. 2015). Agriculture is a prime activity here. Maize, millet, and sorghum are the major staple crops grown in the region. However, farming is predominantly traditional. The Head of the household, usually the oldest male member, makes most of the farm-related decisions (Rivers III et al. 2017). Besides, farmers are mostly poor and perform subsistence farming, and their access to resources is highly limited.

Koutiala houses a large cotton industry that supports local farmers with logistics and training. Since cotton production technologies also help with crop production (Bingen 1998; Cooper and West 2017), local farmers also cultivate cotton to receive such benefits (Dembele et al. 2017). In a way, the cotton industry plays a vital role in the growth of regional agriculture. Food produced here often gets exported to other parts of the country, including the northern region. Since the area plays a critical role in addressing broader food security, it is considered a breadbasket of Mali (Bingen 1998). Ironically, Koutiala has one of the largest food-poor and malnourished populations in the country (Cooper and West 2017; Eozenou, Madani, and Swinkels 2013) that highlights existing disparities in food access at a granular level. Nevertheless, local policy discussions focus on improving food production (Olabisi et al. 2018); discourse on food access remains largely dormant.

3.2 Measuring household vulnerability to food insecurity

3.2.1 Food security: definition and measurement

Food security is dominated by ‘productionist’ arguments (Clapp 2014; Fouilleux, Bricas, and Alpha 2017) where food production has been emphasized for achieving food security. Traditionally regional food production used to be the indicator of food security. However, with globalization and commercialization, food transport got easier, and food-deprived regions like Northern Mali could become equally food secure as the South (Cooper and West 2017; Eozenou, Madani, and Swinkels 2013; Staatz, D'agostino, and Sundberg 1990). This brought food access into the center of food security definition. Recently, food security is increasingly analyzed at more granular levels. Households' or individuals' access to sufficient, stable, and diverse food supply becomes the central theme of current food security definitions. Food security is increasingly defined in terms of its three pillars and a foundation (Figure 3.1): food availability, access, utilization, and stability (FAO 2008).

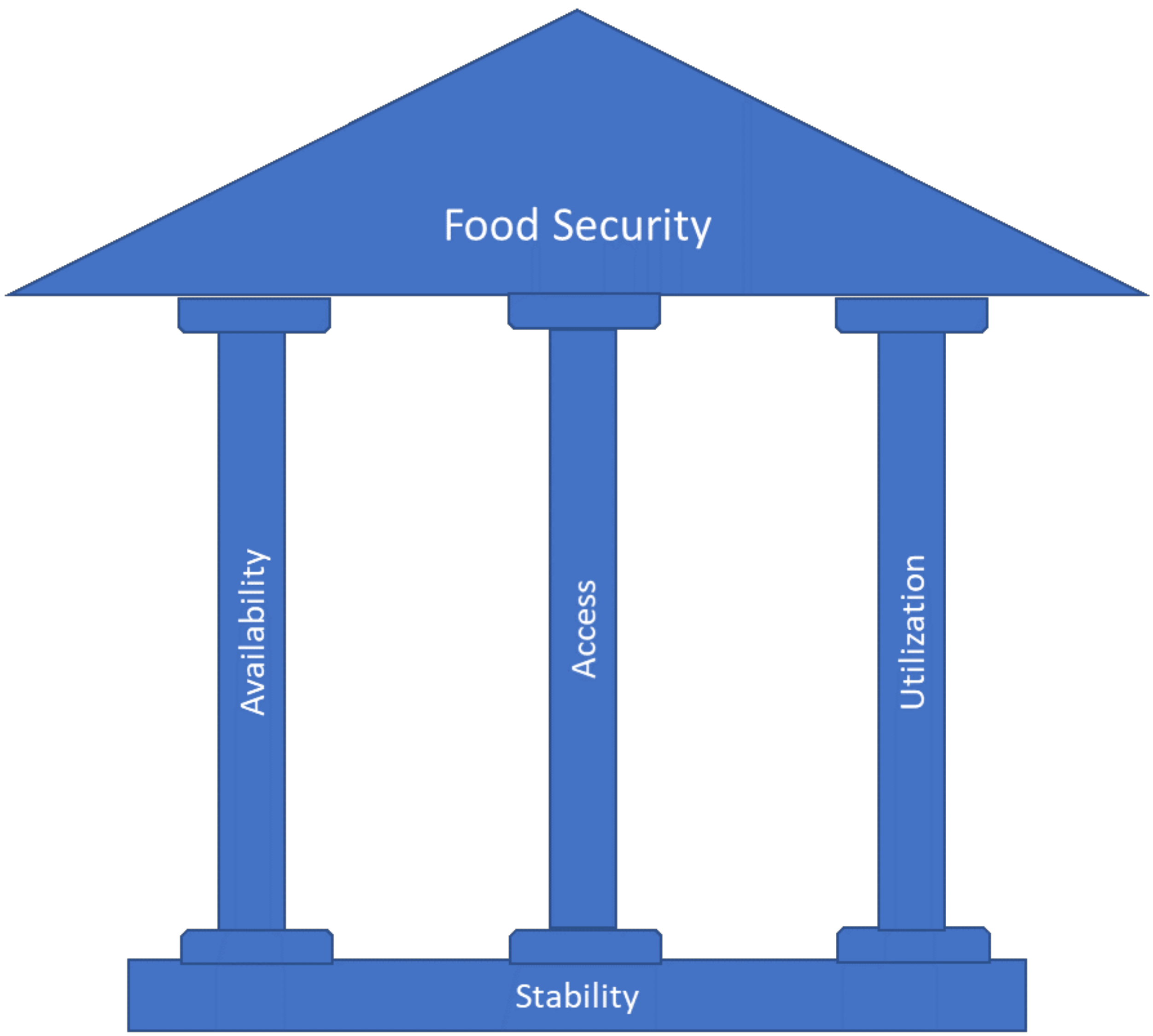

Figure 3.1: The pillars of food security

Since food production indicates food availability, its measurement is generally straightforward.

However, measuring food access and utilization is challenging. Due to the lack of suitable indicators, food access and utilization are usually measured using proxies. For instance, household assets are often used as a proxy for food access. Wealthy households are assumed to have better access to food and, hence, poorer families are considered vulnerable (S. Maxwell and Smith 1992). Utilization, on the other hand, is often measured using anthropometric indices (Scaramozzino 2006). These indicators are usually expensive to collect and prone to errors (Bickel et al. 2000; Scaramozzino 2006). Subjective experiences with food and hunger (Bickel et al. 2000; Hoddinott 1999) are also increasingly used to analyze food security. Although they are easier to collect, subjective indicators are bias-prone and often unreliable for making future projections.

3.2.2 Measuring vulnerability to food insecurity

The notion of vulnerability differs across disciplines but is often considered as synonymous to poverty (Chambers 1989; Scaramozzino 2006). However, Chambers (1989) dichotomizes poverty and vulnerability - the first indicates a lack of resources, while the latter is a defenseless state. Specific groups of people like the elderly, pregnant women, and children are increasingly vulnerable to stresses regardless of their economic conditions (Kelly and Adger 2000). Furthermore, there are external and internal sides of vulnerability. The external side indicates shock, and the internal side of vulnerability is a defenseless state (Chambers 1989). Watts and Bohle (1993) extend this idea and define vulnerability in terms of exposure to risk (external), the capacity to cope (internal), and the ability to recover (internal). Risk exposure does not necessarily indicate a vulnerable state, as long as one can cope with it. However, coping can impede future recovery potential.

Based on Watts and Bohle's approach, we define vulnerability to food insecurity at the interface of biophysical and socioeconomic systems (Figure 3.2). The biophysical environment generally offset food availability by affecting household food production, while socioeconomic factors influence households' access to food. Households look for options to feed their family when exposed to food shortages. These measures (coping strategies) can vary by geography, culture, and severity but usually start with easily accessible low-impact approaches such as meal rationing and in-kind help

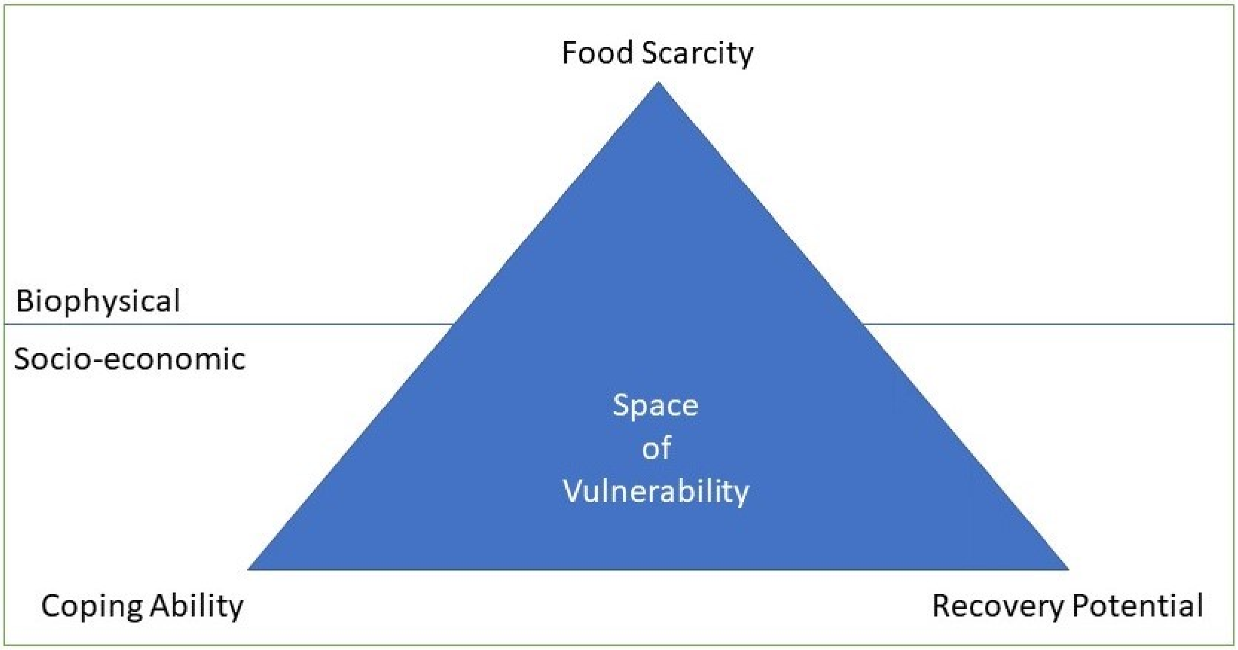

Figure 3.2: Space of Vulnerability (Adapted from Watts and Bohle, 1993)

from relatives or neighbors (S. Maxwell and Smith 1992). However, as the severity of food scarcity increases, households need to resort to more drastic measures, including the sale of household assets and migration (Figure 3.3). Such approaches generally put a strain on domestic resources that can affect households' ability to cope with future food scarcity (D. G. Maxwell 1996; S. Maxwell and Smith 1992).

Vulnerability assessment provides early warning and helps with target identification for relief planning and emergency management (Flanagan et al. 2011; Füssel and Klein 2006; Riely 2000). Disaster management literature uses several vulnerability indices for social (Flanagan et al. 2011), economic (Guillaumont 2009), and climatic (Pandey and Jha 2012) stresses. However, indices specific to food security are highly limited. Existing food security vulnerability indices often work at macro-levels (e.g., Burg 2008; Krishnamurthy, Lewis, and Choularton 2014) and fail to represent household level vulnerabilities. Moreover, these indices focus on current vulnerabilities. Future predictions generally use trend extrapolations that are unreliable as they ignore the dynamics of associated systems (Burg 2008). Since vulnerability is dynamic and complex, it demands an index that captures the dynamics of the complex systems (Riely 2000).

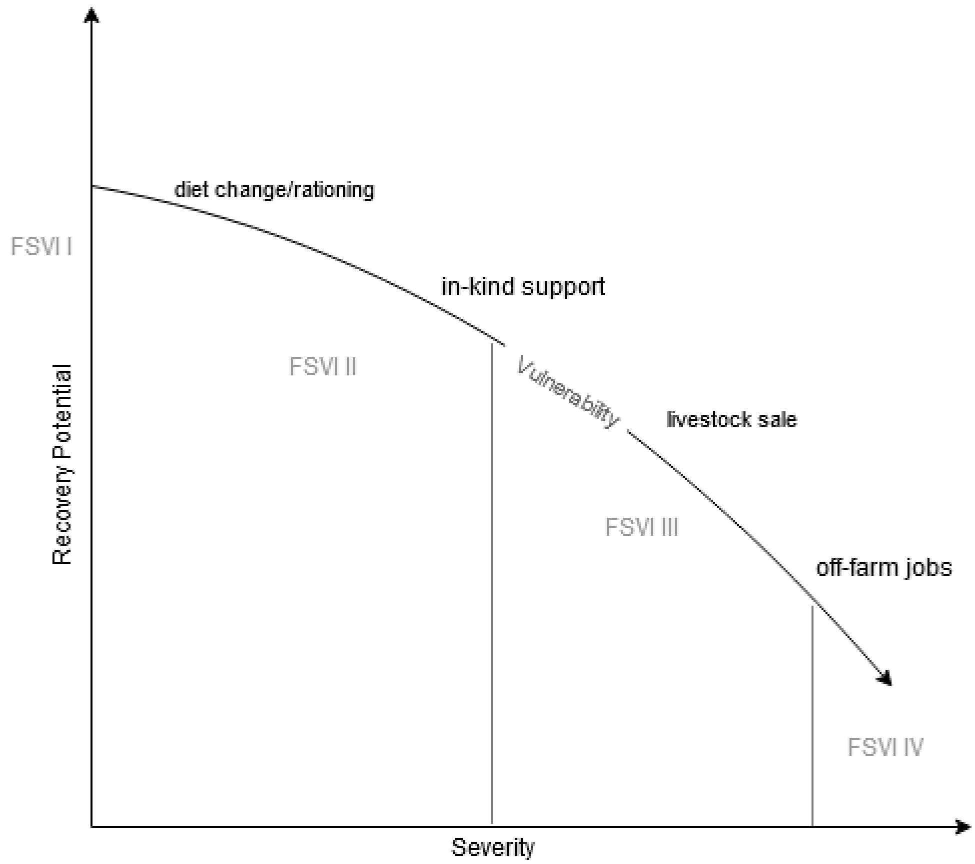

Figure 3.3: Household responses to food shortages (based on FGD and Maxwell 1992)

Despite recognizing food security as a function of food availability, access, utilization, and stability, literature still lacks an index that simultaneously checks all the dimensions of food security. Besides, vulnerability to food insecurity results from complex and dynamic interactions between biophysical and social systems and is difficult to quantify (Krishnamurthy, Lewis, and Choularton 2014). The FSVI, used in the study, is a simple coping-based index that provides vulnerability information based on the coping mechanisms households use to address their food scarcities. Furthermore, we integrate it into the ABM to effectively capture systems complexities needed to explore future vulnerabilities.

The FSVI has four severity[1] levels (Table 3.1). It evaluates food **availability** by analyzing household food production and food **access** by examining their interactions. Similarly, it checks

[1]Since current severity also affects future vulnerability, we use severity and vulnerability interchangeably in the paper.

Table 3.1: Food Security Vulnerability Index (FSVI)

Index	Description
FSVI I	Food secure - households have sufficient food production/availability to feed their family.
FSVI II	Slightly food insecure – households face slight shortages that can be covered by rationing or in-kind help from neighbors and relatives.
FSVI III	Moderately food insecure – households need to purchase food. They might have to sell their assets or go for off-farm jobs.
FSVI IV	Severely food insecure – households deplete all their domestic resources. Members gone for off-farm jobs decide to migrate, creating work-force shortages at home and further exacerbating household's food insecurity.

household calorie sufficiency for evaluating **utilization**. The longitudinal ABM simulations, in turn, provide information on the **stability** of household food supply. The highlighted terms constitute a comprehensive approach to food security (Figure 3.1). Maxwell and the team (D. Maxwell, Caldwell, and Langworthy 2008; D. G. Maxwell 1996; D. Maxwell, Watkins, et al. 2003) are big proponents of coping-based indices for measuring food security. According to them, these indices work as 'current' as well as 'leading' indicators; i.e., beside reflecting the current severity of food scarcity, the indices also indicate households' susceptibility to future vulnerabilities.

3.2.3 Coupled biophysical and social food security analysis

Biophysical and social sciences are highly active but often disjoint in defining food security. Biophysical crop science emphasizes promoting crop productivity for food security (Gebbers and Adamchuk 2010). Social science, on the other hand, attributes food insecurity to unjust resource distribution and access (Jenkins and Scanlan 2001). Household food security requires sufficient food supply supported through stable production and access. Food production is generally influenced by biophysical and climatic conditions and farm management. Food access, on the other hand, relies on resource availability controlled by prevailing socioeconomic policies and practices. Besides, household access to resources also affects farm management.

Hence, food security lies at the intersection of biophysical, climatic, and socioeconomic systems, and requires a broader systems approach for its analysis (Hammond and Dube 2012; J. W. Jones et al. 2017). In this study, we integrate SALUS (Systems Approach to Land Use Sustainability) (Basso, Ritchie, et al. 2006), a bio-physical process-based crop model, with an ABM for a comprehensive household food security analysis. By using the crop model that explores the dynamics of crop production coupled with the ABM of household food system, we aim to capture the interplay between biophysical, climatic, and socioeconomic environments responsible for household food availability and access (Figure 3.4).

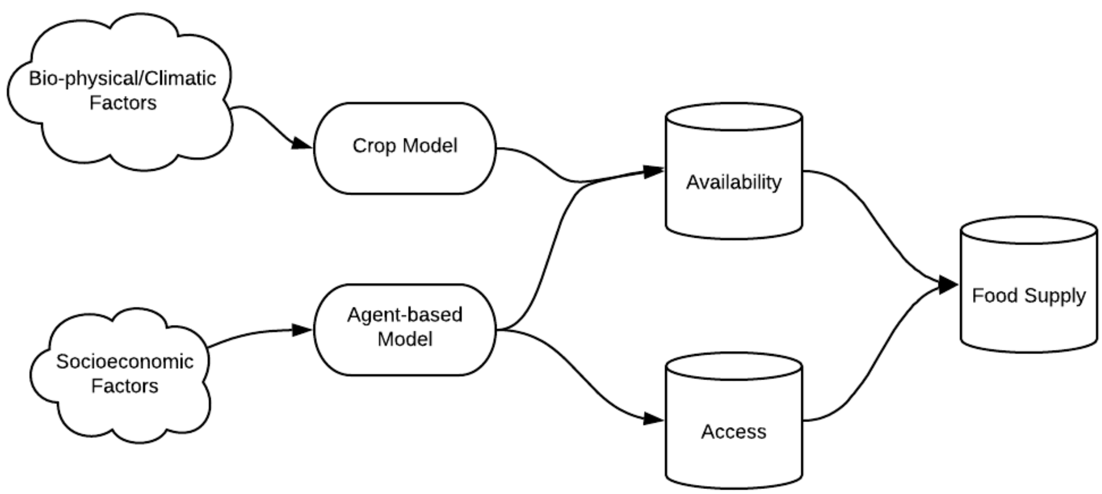

Figure 3.4: An integrated systems approach to food security analysis

3.2.3.1 Crop models for estimating food production

Farmers regularly monitor the growth and development of their crops at different stages of crop cycle to get the real-time evaluation of yield and management. These estimations are often subjective, restricted to small spatial and temporal scales, and are not expandable or transferable (i.e., the same approach cannot be used at different locations). Crop modelers, on the other hand, develop statistical and process-based models that can forecast yields based on empirical biophysical and climatic observations. These models can predict harvests at a much larger extent and are often transferable (Basso and Liu 2019).

Statistical crop models extrapolate past trends to predict future yields. These models are simple and have low data requirements but usually need high-quality data for reliable estimations. Recent advancements in technologies like remote sensing and machine learning have increased the reliability of statistical models (Basso and Liu 2019). However, these models do not capture the complex dynamics of agricultural sub-systems and cannot explain 'out of sample' scenarios (Basso and Liu 2019; J. W. Jones et al. 2017). Unlike statistical approaches, process-based models capture systems complexities, making them useful in exploring plausible future scenarios. Process-based crop models are based on plant responses to physical and bio-climatic variables and are suitable alternatives to statistical models for long-term yield estimations.

The process-based models use agroecological and climatic indicators to evaluate crop biomass. They are modular (Asseng et al. 2014) and contain a series of mathematical equations representing the growth and development of crops. Some of their key processes include phenology, biomass accumulation, and water and nutrient uptake (Asseng et al. 2014). These models are highly useful for evaluating management practices, yield gap, nutrient cycling, environmental impacts, and climate change mitigation and adaptation (Asseng et al. 2014; Basso and Ritchie 2015; Basso, Ritchie, et al. 2006; Basso, Sartori, et al. 2012; Liu and Basso 2017).

SALUS uses a systemic approach (Figure 3.5) to simulate daily plant growth and soil conditions. It consists of three major components – a crop growth module, soil organic matter and nutrient cycling module, and soil water balance and temperature module. The model has been used extensively for simulating crop productivity (Basso and Ritchie 2015; Basso, Sartori, et al. 2012; Liu and Basso 2017) and evaluating farm management and their environmental impacts (Basso, Ritchie, et al. 2006; Basso, Sartori, et al. 2012). However, SALUS has a large data requirement. It generally requires information on physical and chemical composition at each layer of soil, daily weather conditions, crop genetics, and crop management. As a result, using SALUS in developing African countries, where detailed quality data is usually scarce, is often challenging (Liu and Basso

2017).

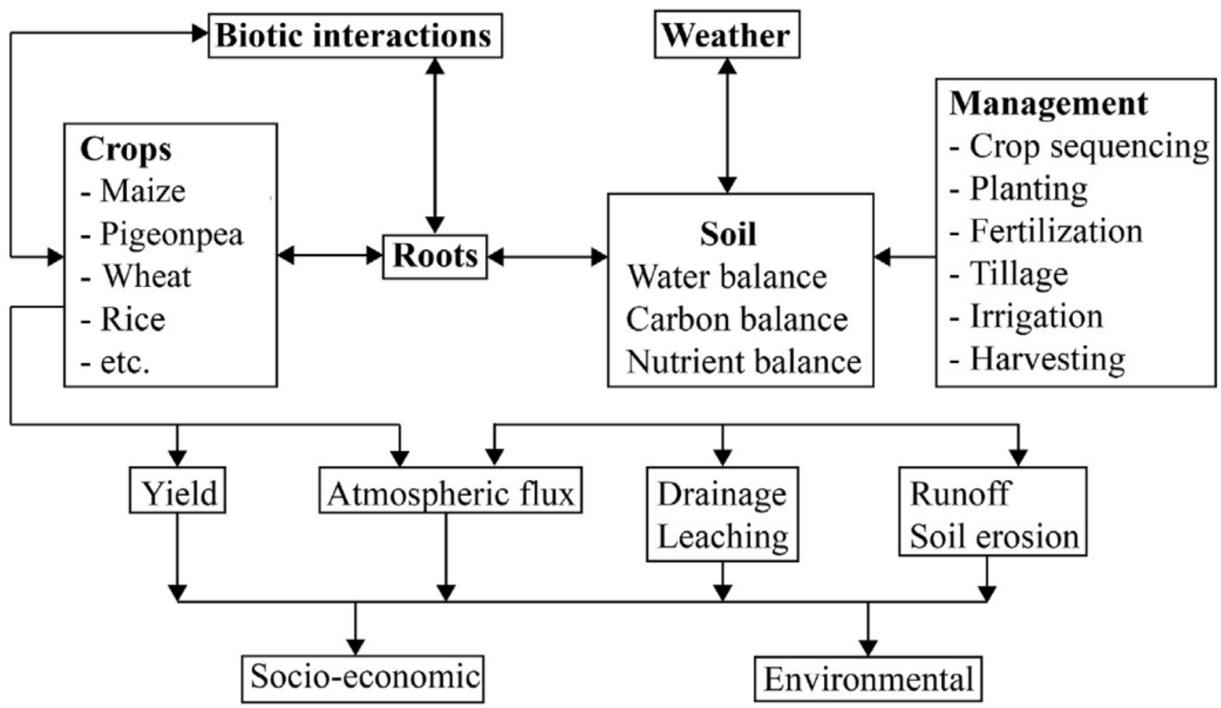

Figure 3.5: A systems approach in SALUS model (Source: Basso, Ritchie, et al. 2006)

A key criticism of crop sciences is their total fixation on crop production, ignoring the social dimensions of food security (James W Jones et al. 2017). Furthermore, the crop models generally treat farmers as rational 'homo-economicus'. They supposedly have the knowledge and resources to optimally exploit the productivity of their farms completely. However, farmers are neither uniformly capable and knowledgeable; nor do all want to maximize productivity. Hence, one needs to consider household heterogeneity and bounded rationality for a reliable food security analysis.

3.2.3.2 Integrating ABM for food security analysis

ABM is useful for understanding phenomena that emerge from complex and nonlinear interactions of autonomous as well as heterogeneous social constituents of a system (An et al. 2005). ABM can adequately consider population heterogeneity and bounded rationality, and is highly useful in analyzing food security (An et al. 2005; Bithell, Brasington, and Richards 2008; Kennedy 2012). It has been widely used in evaluating land management (Ligmann-Zielinska 2009) and its repercussion on food production (T. Berger and Troost 2014; Magliocca, D. G. Brown, and Ellis 2013; Polhill, Sutherland, and Gotts 2010). Since ABM can handle social interactions well, it can naturally analyze food access (Koh, Reno, and Hyder 2019).

In Mali, rural households are mostly subsistence farmers. Thus, capturing food production is essential for rural food security analysis. However, ABM, being primarily a model of the social system, cannot capture crop dynamics. Coupling a process-based crop model with an ABM of household food system incorporates the dynamics required for an effective and comprehensive food security analysis. However, literature severely lacks integrated crop-ABM models for food security analysis. Most of the integrated models focus on the impacts of policies and practices on land and farm management and their effects on household food production and economy. For instance, the People and Landscape Model (Matthews 2006) integrates a process-based crop model with an ABM to analyze crop-nutrient management. Marohn et al. (2013) used Land Use Change Impact Assessment (LUCIA), a process-based crop model, with a Multi-Agent System to evaluate soil conservation strategies in Vietnam. Similarly, Schreinemachers and Thomas Berger (2011) integrated a Mathematical Programming-based Multi-Agent System with biophysical models to examine the effects of agricultural technologies, market dynamics, environmental change, and policies on household and agroecological resources. Earlier research by them (Schreinemachers, Thomas Berger, and Aune 2007) used ABM with the Tropical Soil Fertility Calculator (TSPC) to simulate the effect of crop productivity on household economy.

A more recent integrated food security analysis, done by Wossen and Thomas Berger (2015), used a crop model with an ABM to analyze the impacts of climate and price fluctuations on household food availability and access. However, their research does not check the stability aspect of food security as it lacks long-term climate and market projections. Recently, Dobbie et al. (2018) looked at all four dimensions of food security for community food security analysis using crop and agent-based models. They integrate climate change scenarios in their study to simulate future crop production. However, they do not use a process-based crop model and represent crop yield as a function of input and water availability. Although crop productivity is profoundly affected by temperature, their model does not capture such dynamics. Additionally, they used RCP 2.6, a 'highly stringent' climate change scenario, which only simulates a best-case future. Our research addresses these gaps by capturing all four dimensions of food security by integrating a process-based crop model with an ABM. Additionally, we use a high emission RCP 8.5 climate change scenario that helps with risk estimation and planning interventions.

3.2.3.3 Model parameterization, setup, and evaluation:

Agents in the ABM represent farm households in Koutiala. The households are represented in the landscape by vector polygons (representing households' land parcels) of different shapes and sizes. We develop a simple GIS model for creating the distributions of land parcels. GIS places the parcels randomly in and around arable land. Additionally, the GIS model is set to place the land parcels denser and smaller within urban areas reflecting their distribution in reality (N'Danikou et al. 2017). We divide households into the following four categories based on the size of their land parcels (Falconnier et al. 2015):

1. High Resource Endowed – Large Herds (LRE_LH) households
2. High Resource Endowed (HRE) households
3. Medium Resource Endowed (MRE) households
4. Low Resource Endowed (LRE) households

Koutiala has only one growing season; households partition their farmland to cultivate different crops. We use SALUS to simulate the cultivation of maize, millet, and sorghum. At the beginning of a model run, the ABM randomly selects one set of land parcels generated by the GIS model. The ABM then receives the productivity estimates from SALUS and interpolates the values to the land parcels. The model then calculates household food production and evaluates food sufficiency (Figure 6). Food sufficient families are labeled as food secure households (FSVI I), and food insufficient households look for coping alternatives beginning with in-kind help from close neighbors or relatives. The families whose food deficiency is addressed by in-kind support get labeled as slightly food insecure (FSVI II) and the households that need to purchase food are moderately food insecure (FSVI III). Households either sell their livestock or go for off-farm jobs to purchase food. The households that deplete their internal resources (i.e., livestock and workforce) are labeled as severely food insecure (FSVI IV).

For the model simulations, We define a 'business-as-usual' scenario based on the current trends in climate change, population growth, and farmers' access to input. We select a high emission climate change scenario (Representative Concentration Pathway – RCP 8.5) (Riahi et al. 2011). Similarly, the population growth rate for Koutiala is set at 5% per annum (Farvacque-Vitkovic et al. 2007; Dijk, Bruijn, and Beek 2004). During our focus group discussions, the local farmers highlighted the issue of the lack of access to agricultural input. Farmers usually produce manure for their fields using household and agricultural residues. Based on the discussions, we set the input application at 1T/ha of manure. We use the Met Office Hadley Centre ESM (HadGEM2-ES) (C. Jones et al. 2011) climate change model to generate future weather conditions for the crop model. Daily estimated weather data is obtained from Marksim DSSAT weather file generator (http://gismap.ciat.cgiar.org/MarkSimGCM). Although the region lies within a uniform Sudano-Guinean agroecological zone, to account for local variability in weather (albeit small), we divide our study area into four quadrants and use their centroids as weather stations.

Each model simulation runs for 40 years (from 2010 to 2050) with one-year timesteps. SALUS is run for the entire Koutiala landscape containing 690,000 grids of 250m spatial resolution. SALUS outputs are validated using reported field data (Table 3.2). ABM is generated from stakeholder validated ABM structure (Appendix D). We applied standard verification including methods such as unit tests, extreme tests, assertions, and debugging (An et al. 2005; Gilbert 2019). We run 1000 ABM simulations for the business-as-usual scenario. The ABM is developed in Python 3.7 programming language (`https://www.python.org/`) using multiple libraries, including Pandas, GeoPandas, and Rasterio. ABM parallelization is achieved through the concurrent.futures library. Since both crop and agent-based models are extensive and resource-intensive, we used High Performance Com-

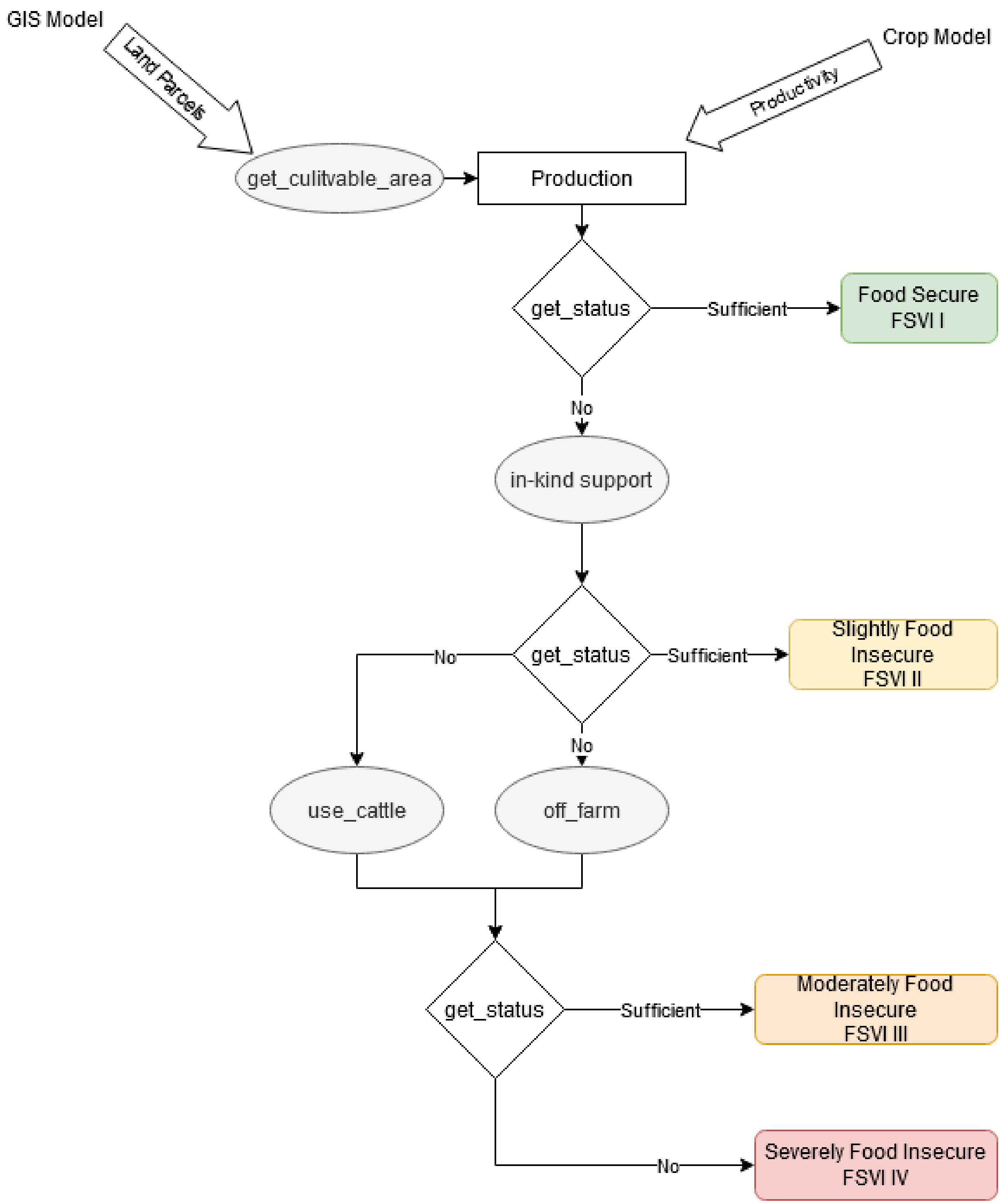

Figure 3.6: Structure of Crop-ABM coupled Model

Table 3.2: Koutiala crop yields (reported) (Source: Cellule de Planification et de Statistique, Mali)

Year	Millet Yield (Kg/ha)	Sorghum Yield (Kg/ha)	Maize Yield (Kg/ha)
2003	958	1059	1800
2004	921	994	1804
2005	983	989	1773
2006	979	991	1896
2007	1000	1095	2040
2008	1100	1150	2000
2009	1000	1100	2300
2010	1000	1100	2500
2011	892	710	2285
2012	900	1000	2214
2013	979	955	2118
2014	1050	1106	2475
2015	1046	1099	2896
2016	1025	1066	2440

puting (HPC) at Michigan State University for the simulations. Detailed information on the ABM is presented in the ODD format (V. Grimm et al. 2006; Volker Grimm et al. 2010) in Appendix E, and the details on SALUS can be found at `https://basso.ees.msu.edu/salus/index.html`. Additionally, itemized model parameters are presented in Table 3.3 and Table 3.4..

Table 3.3: SALUS Parameters

SALUS Parameterization			Source
Soil	**Parameters**	**Resolution**	International Soil Reference and Information Center (http://www.isric.org)
Physical Properties	Bulk density, Clay content, Coarse fragments, Sand, Silt	250m	
Chemical Properties	Cation exchange capacity, Nitrogen, Soil Organic Carbon, pH	250m	
Weather/Climate	**Parameters**	**Resolution**	Marksim DSSAT weather file generator (http://gismap.ciat.cgiar.org/MarkSimGCM)
Weather data	Tmax, Tmin, Rainfall, Solar radiation	Daily	
Future Climate	RCP 8.5 (HadGEM2-ES)	-	
Farm Management	**Parameters**	**Value**	Focus Group Discussion/ Expert Advice/ (Soumaré et al. 2002)
Crops	Maize, Millet, Sorghum	20%, 40%, 40% of total land respectively	
Input	Barnyard Compost	1T/ha	

Table 3.4: ABM Parameters

ABM Parameterization					Source
Total Farm Households (No of Agents)		9000			Census (2009)
HH typologies	**Distribution**	**Land_size: mean (std)**	**HH_Size: mean (std)**	**Livestk: mean (std)**	(Falconnier et al. 2015)
High Resource Endowed - Large Herdsize (HRE_LH)	13%	16.6 (8.33)	45.3 (18)	5.7 (1.5)	
High Resource Endowed (HRE)	28%	11.8 (6)	27.3 (6.6)	2.7 (1.6)	
Medium Resource Endowed (MRE)	40%	7.5 (2.4)	12.6 (1.7)	4.1 (6.5)	
Low Resource Endowed (LRE)	19%	3.2 (2)	7.9 (4.9)	1.3 (1)	
Food supply	**Values**				
Calorie demand	2400 per person				FAO (http://www.fao.org/)
Calorie supply	3100 per kg maize; 3550 per kg sorghum/millet				
Sale of 1 cattle provides	1285 kg of grain				Derived from ICRISAT, 2017
Food Production	**Values**				
Workforce available	1/2*hh_size				(Ruben et al. 1997)
Worker-days required (Crops)	63				
Worker-days required (Cotton)	149				
Food Access	**Distribution**				
Neighborhood distance	Uniform 2000,3000,4000 (meters)				based on Focus Group Discussion
Neighborhood support	Discrete (0%, 5%, 10%, 20%) % of surplus	P(0.1,0.5,0.3,0.1)			

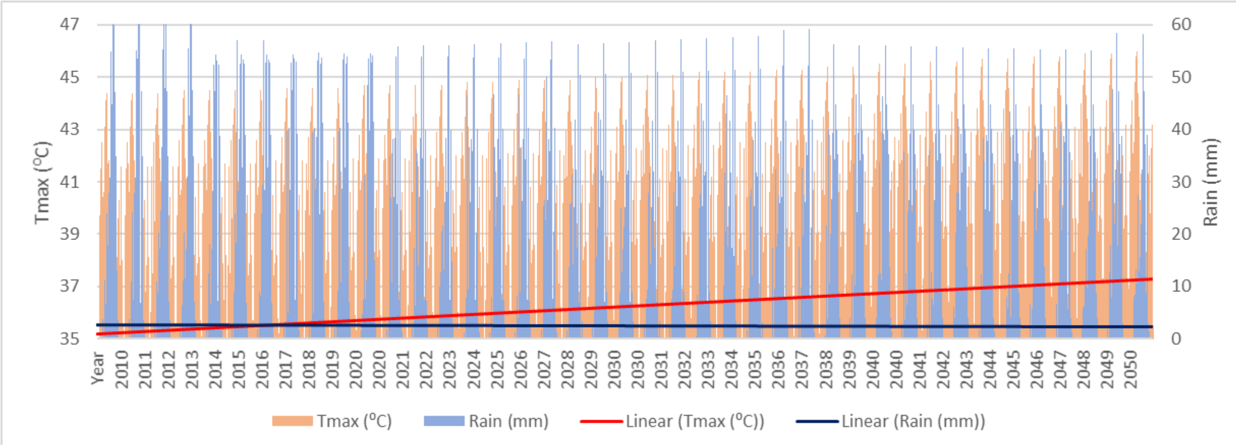

Figure 3.7: Future climate under RCP 8.5 scenario

3.3 Results and Discussions

The climate model predicts a warmer Koutiala; its mid-century temperature could rise by more than 2°C (Figure 3.7). Temperature increase accelerates plant phenological development and shortens the growing season. This can lead to reduced biomass accumulation (S. Asseng et al. 2017; Basso, Kendall, and Hyndman 2013). Bassu et al. (2014) suggested that with every °C increase in temperature maize productivity could decline by 0.5T/ha. Since Koutiala is expected to see an increase in future temperature, crop productivity is likely to decline. The region experiences no significant changes in future rainfall patterns. However, increased temperature causes increased evapotranspiration (Roudier et al. 2011) that can limit water availability to plants. Our SALUS modeling produced results where maize and sorghum suffered from water stress, and their future yields declined by more than 40% (Figure 3.8). Since millet is more water-efficient than maize and sorghum (Saxena et al. 2018; Schlenker and Lobell 2010), it showed no water stress in the model. Millet productivity remained relatively stable, with a mere 2% decline in its future yields. We also found that southern Koutiala was more productive than the north (Figure 3.9). However, the region would significantly lose its productivity in the future (Figure 3.10).

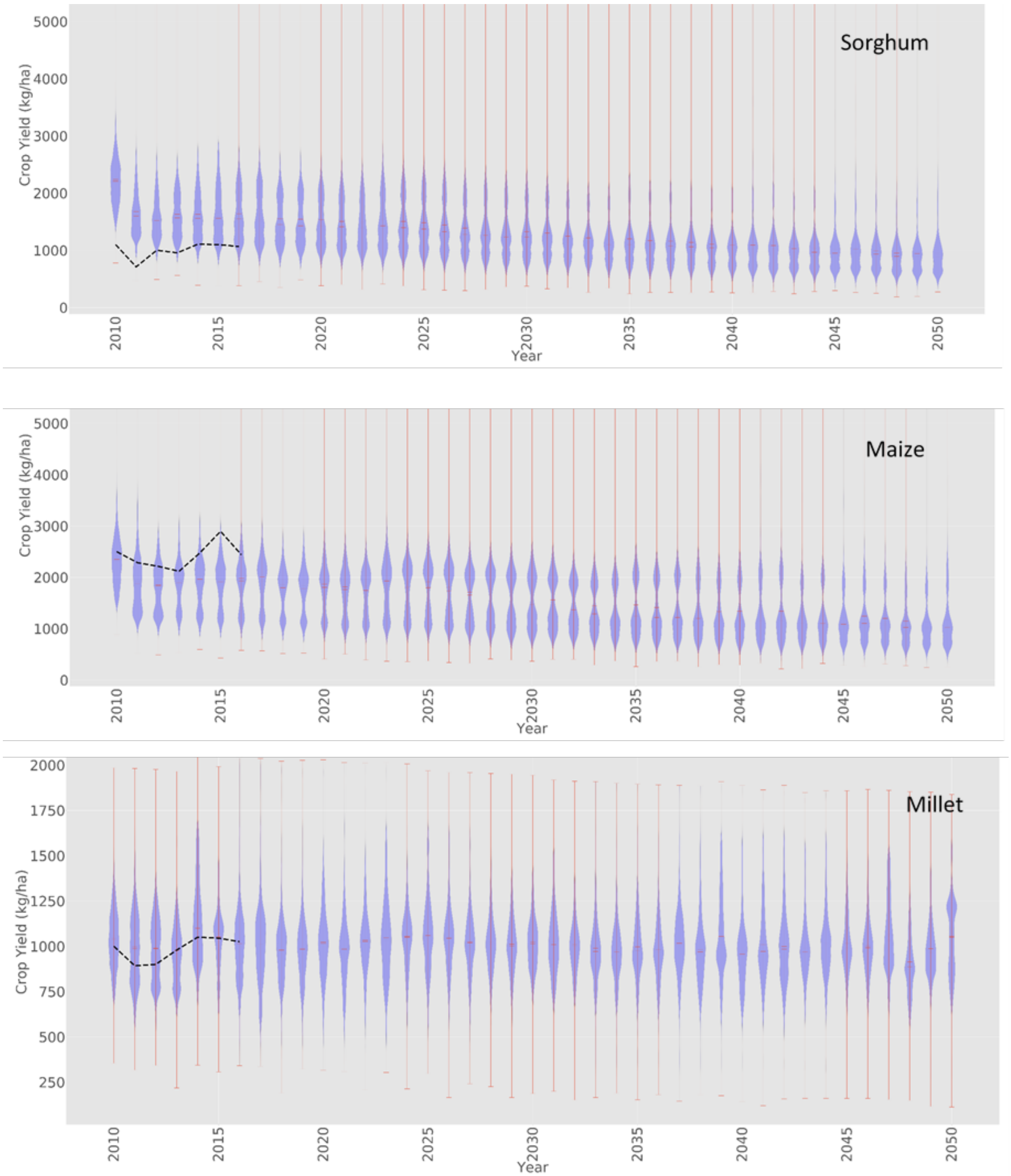

Figure 3.8: SALUS predicted yields (kg/ha) for business-as-usual scenario (dashed lines represent field reported data)

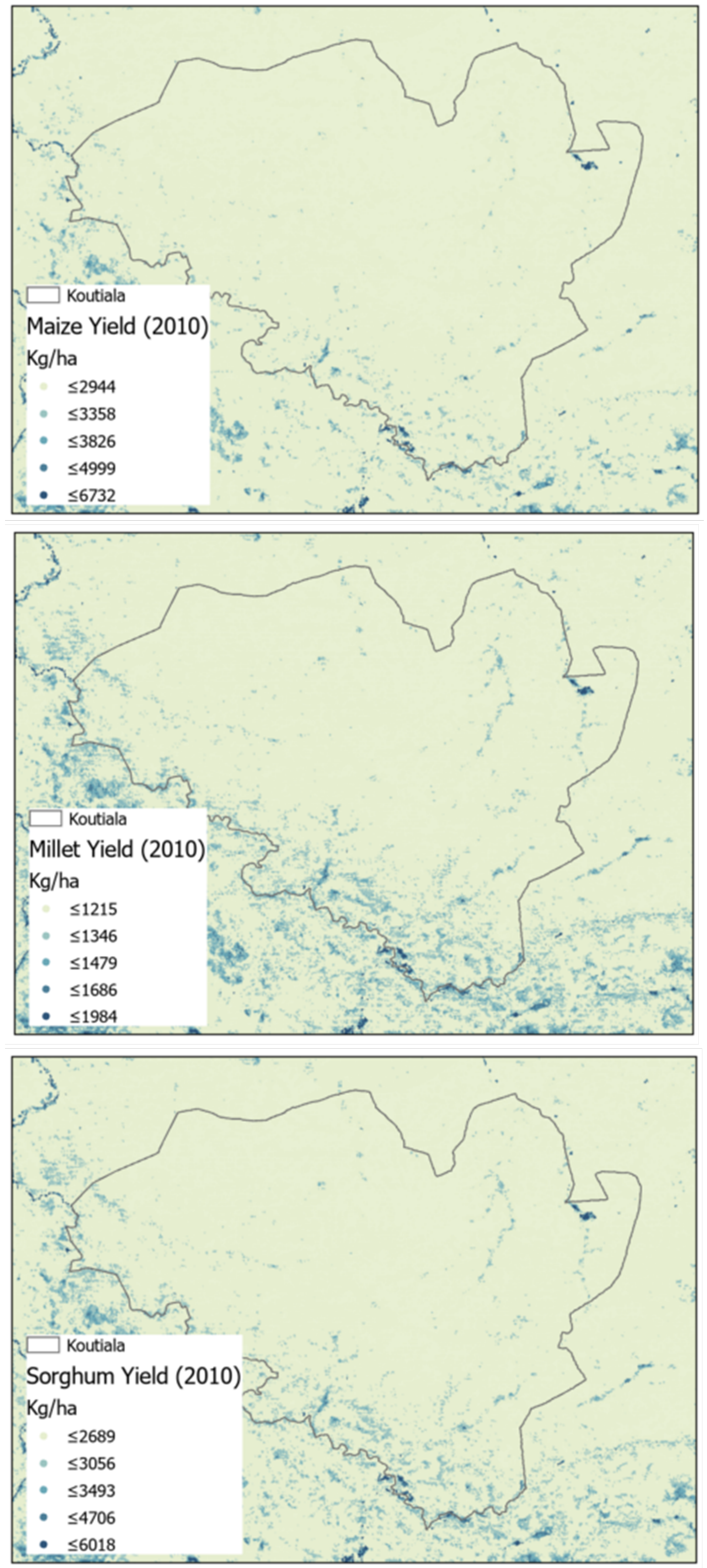

Figure 3.9: Spatial distribution of crop productivity in Koutiala

The crops we simulated belong to C4 plant categories. These plants are highly resistant to heat and drought (Roudier et al. 2011). Still, SALUS predicted a significant decline in their future productivity, especially for maize and sorghum. Farm management plays a vital role in plant water use efficiency (Basso, Kendall, and Hyndman 2013; Ritchie and Basso 2008). The lack of improved technologies and farm management predominant in the region were not effective in reducing crop water stress. Additionally, these plants are less sensitive to atmospheric CO_2 (Roudier et al. 2011; Schlenker and Lobell 2010). Although RCP 8.5 has a high level of CO_2, its benefits on the productivity of the crops have been minuscule.

Koutiala is witnessing population growth higher than the national average (Farvacque-Vitkovic et al. 2007; Dijk, Bruijn, and Beek 2004). At this rate, the region is likely to see a significant increase in its baseline population by 2050. Increased population, together with reduced crop productivity, substantially offsets regional food balance. We found that the regional cumulative food demand would surpass its food production by 2025 (Figure 3.11). This can severely impact the region's food export, jeopardizing its status as the breadbasket of the country. However, the ABM revealed that household food insecurity, defined by using the FSVI, existed well before 2025. It further signifies the inadequacy of regional food availability in reflecting household food security.

Similarly, we found that almost 80% of the households were likely to be food insecure by 2050 (Figure 3.12). For the subsistence farmer in the region, household food production is critical. The households in the less productive north were found to be more susceptible to food insecurity than their counterparts in the South (Figure 3.13). Additionally, population dynamics play an important role in household food security. Population growth increases food demand to a level that some households cannot easily meet. The model revealed a higher number of FSVI II than FSVI III households at the beginning of the simulation, indicating that the food shortages were small with a smaller population. However, it was later superseded by FSVI III households that needed food purchases to feed the family. The model identified larger households (HRE_LH and HRE) to be more dependent upon food purchases (Figure 3.14)

However, population growth is not all doom and gloom. Traditionally, rural households in

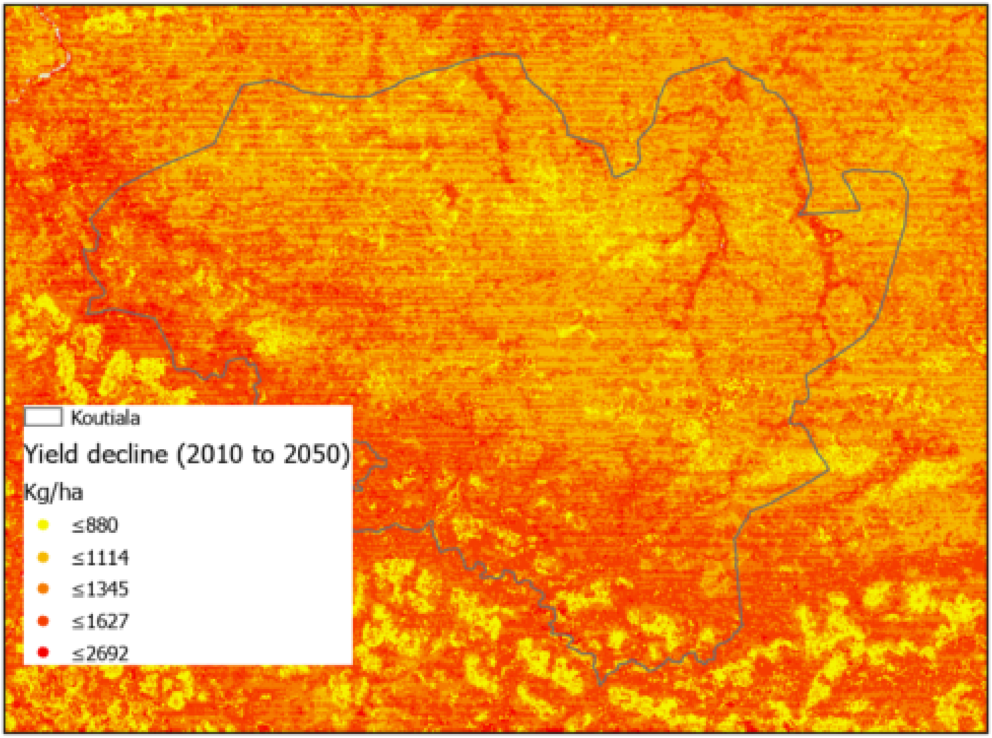

Figure 3.10: Maize productivity decline from 2010 to 2050 (kg/ha)

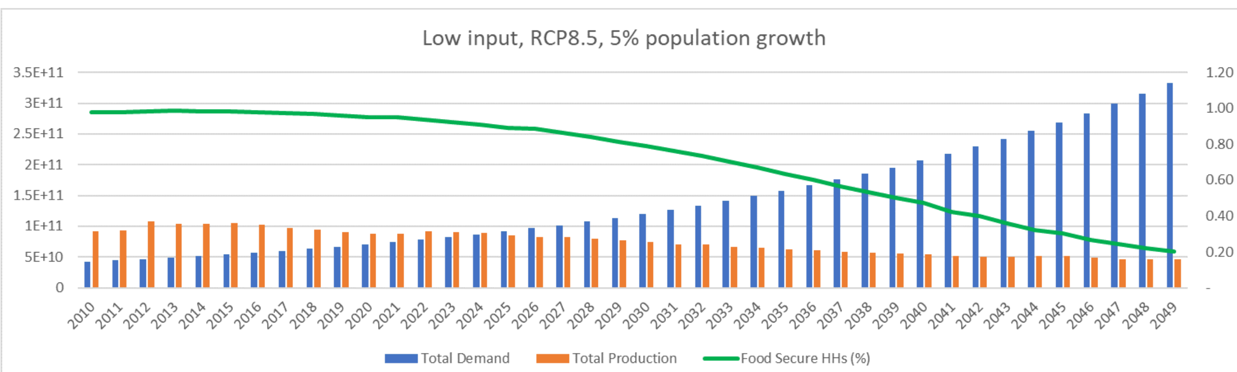

Figure 3.11: Regional food production vs. demand

Koutiala are large and contain extended family members living and working together. Since farming is mainly manual, a large family usually means the availability of a large agricultural workforce. Older generation in the region still prefers the traditionally large households (Rivers III et al. 2017). The large households often have sufficient workforce for farm and off-farm jobs. Although they were found to be prone to food insecurity in the study, the large households usually had resources – in the form of workforce and livestock - to address the problem. This prevents them from being severely food insecure (FSVI IV). However, smaller households have highly limited livestock and workforce for farm and off-farm jobs. Any depletion of domestic resources could easily expose them to severe forms of food insecurity (Figure 3.14).

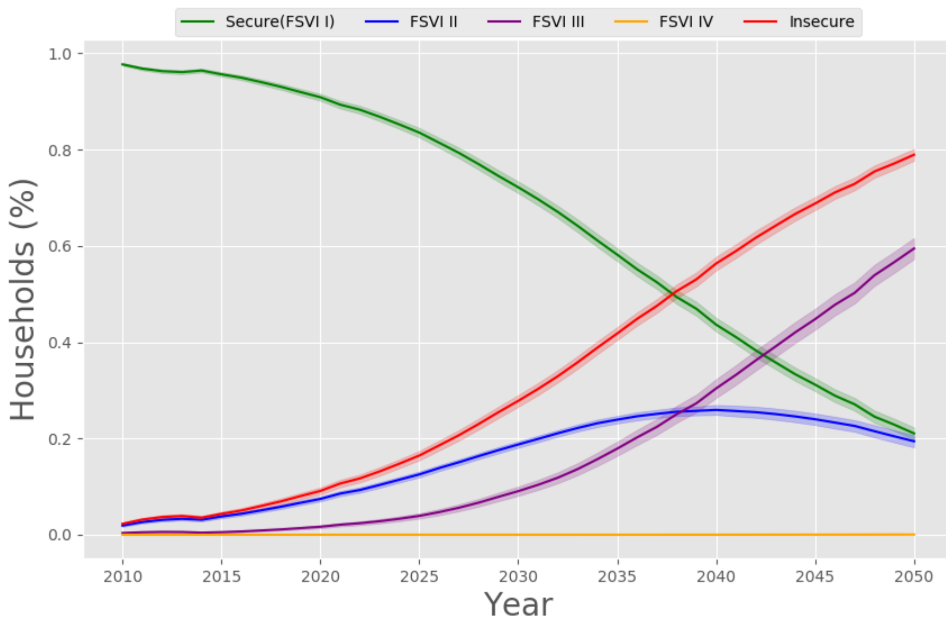

Figure 3.12: Trajectory of food security

3.4 Limitations and future development

There is only one-way communication between SALUS and the ABM; the ABM uses outputs from the crop model as its inputs. Due to this loose coupling, incorporating some dynamics are challenging (Parker, Hessl, and Davis 2008). Households learn from their experience, and farming evolves over time. Our model considers farm management uniform across time and space. Learning and adaptation, some of the most critical characteristics of ABM, are not incorporated in the model. Future updates to the model should integrate such dynamics through tighter integration between SALUS and ABM. This enables the crop model to receive farming information from ABM in real-time.

Similarly, post-harvest crop loss and loss due to pests and diseases are not considered in the model. Households consume fruits, vegetables, and animal products. However, non-cereal food is

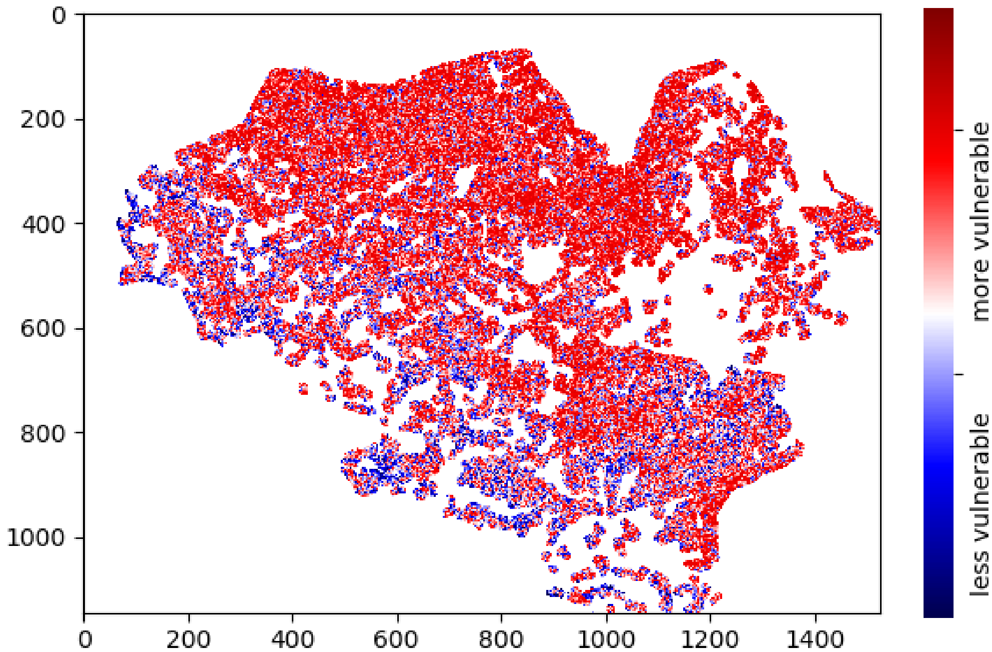

Figure 3.13: Spatial distribution of vulnerability to food insecurity

not included in the calorie calculation. Additionally, calorie requirements and access are considered uniform across household members.

Almost all farm households in Koutiala cultivate cotton. In our model, we did not explicitly incorporate non-farm income and income from cash-crops. According to Cooper and West (2017), only a small portion of such income is used for food purchases. Our model considers households having minor food deficits (less than 5% of total food demand) as food secure, assuming that such income will cover these shortages.

Figure 3.14: Vulnerability to food insecurity by household types

Furthermore, the model assumes a constant population growth. In reality, resource availability dictates growth (A. Ford and F. A. Ford 1999). The population might not be able to grow continuously at the current rate under food scarcity. Similarly, the ABM agents are farm households only; non-farm households and other stakeholders are not considered in the model. Other agents of the food security system like government/non-government agencies, credit agencies, and extension workers should also be included in the updated model.

3.5 Conclusion

Productionist arguments dominate food security discourse. Food production is, indeed, essential for food security. However, adequate food access is also necessary, especially for attaining food security at the household level. Household food security analysis, therefore, primarily needs to look at both household food production and access. We integrate a crop model with an ABM of household food systems for a comprehensive evaluation of household food security. The coupled model allows us to explore food security at the intersection of biophysical, climatic, and socioeconomic systems. Additionally, the model has the granularity, heterogeneity, and complexities needed to effectively analyze future food security at the household level.

Households usually find ways to address food scarcity at home. The measure they use reflects not only the current severity but also their future vulnerability. Food security is inherently dynamic and non-binary. The use of FSVI integrated with ABM allows us to explore the dynamics and nuances of household food security. We find that the majority of regional households will be food insecure in the future. Large families, especially, are more susceptible to food insecurity. In contrast, smaller households are prone to higher severity of food insecurity. Also, the spatial feature of the coupled model highlights the areas prone to food insecurity. Such information has broad policy implications, especially for target identification and intervention.

APPENDICES

APPENDIX D

PICTORIAL CONCEPTUAL DIAGRAM USED FOR STAKEHOLDER EVALUATION

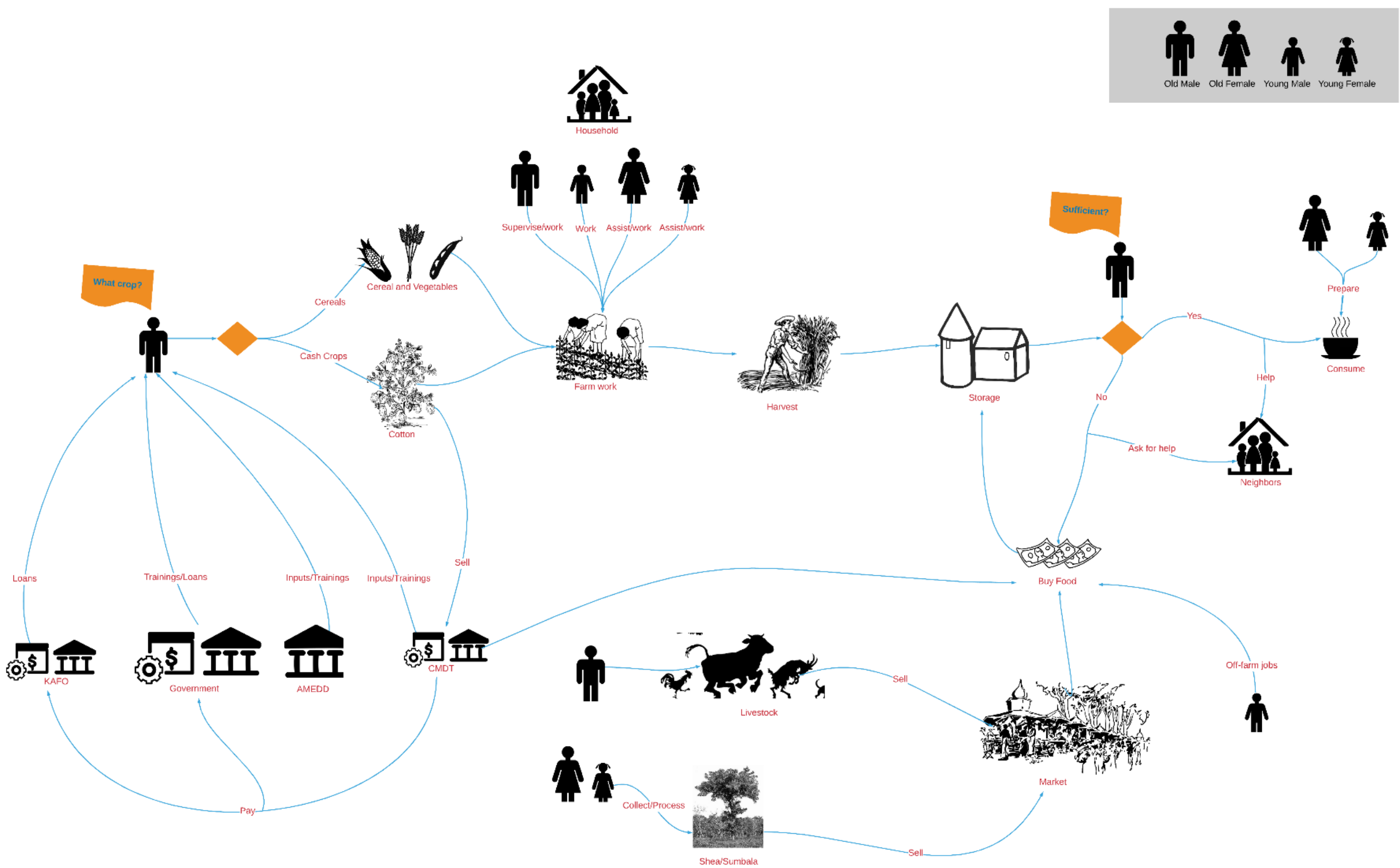

Figure D.1: Pictorial conceptual diagram used for stakeholder evaluation

APPENDIX E

ABM DESCRIPTION IN ODD FORMAT

The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models.

E.1 Purpose

The ABM explores the effect of biophysical and socioeconomic factors on household vulnerability to food insecurity. For a comprehensive food security analysis, the model looks at household food availability, access, utilization, and stability. It is coupled with a process-based crop model that provides the information on household food productivity. Using the information, the ABM evaluates household food production, checks for sufficiency, and looks for coping options during food shortages. Household vulnerability is measured by evaluating recovery potential of the options used for coping food shortages.

E.2 Entities, state variables, and scales

Agents: Agents represents rural farm households in Koutiala district of Southern Mali. They are represented in the model by vector polygons (i.e., their farmland) of different shapes and sizes distributed randomly across the landscape. Households work towards securing food for their family. There are the following four types of households (Falconnier et al. 2015):

- High Resource Endowed – Large Herd size (HRE_LH) households
- High Resource Endowed (HRE) households
- Medium Resource Endowed (MRE) households
- Low Resource Endowed (LRE) households

The agents contain following state variables:

Table E.1: State variables used in the ABM

Entity	Sub-group	Variable name	Description	Possible Values	Units/Notes
Household	HRE_LH	HH_size	size of the households	45.3 (18)	>4 in a household
		Livestk	number of the livestock	5.7 (1.5)	>= 0
		Land_ha	household land size	16.6 (8.3)	Ha / (2-100 ha)
		Neigh_dist	neighborhood distance	2000,3000,4000	meters
		Neigh_support	portion of food saved for supporting the neighbors	0,0.5,0.10,0.20	%
		FSVI	Food Security Vulnerability Index	I - IV	
	HRE	HH_size	size of the households	27.3 (6.6)	>4 in a household
		Livestk	number of the livestock	2.7 (1.6)	>= 0
		Land_ha	household land size	11.8 (6.2)	Ha / (2-100 ha)
		Neigh_dist	neighborhood distance	2000,3000,4000	meters
		Neigh_support	portion of food saved for supporting the neighbors	0,0.5,0.10,0.20	%
		FSVI	Food Security Vulnerability Index	I - IV	
	MRE	HH_size	size of the households	12.6 (1.7)	>4 in a household
		Livestk	number of the livestock	4.1 (6.5)	>= 0
		Land_ha	household land size	7.5 (2.4)	Ha / (2-100 ha)
		Neigh_dist	neighborhood distance	2000,3000,4000	meters
		Neigh_support	portion of food saved for supporting the neighbors	0,0.5,0.10,0.20	%
		FSVI	Food Security Vulnerability Index	I - IV	
	LRE	HH_size	size of the households	7.9 (4.9)	>4 in a household
		Livestk	number of the livestock	1.3 (1)	>= 0
		Land_ha	household land size	3.2 (2)	Ha / (2-100)
		Neigh_dist	neighborhood distance	2000,3000,4000	meters
		Neigh_support	portion of food saved for supporting the neighbors	0,0.5,0.10,0.20	%
		FSVI	Food Security Vulnerability Index	I - IV	

Spatial Units: One household owns only one land parcel. The land parcels are of various sizes ranging from 2 ha to 100 ha. The crop model simulates biophysical and climatic conditions to estimate crop productivity of the land parcels.

Temporal Units: The model is run for 41 years (from 2010 to 2050) and one timestep represents one year.

Environment: Since crop production influence households' interactions and behavior, crop yield represents model environment.

E.3 Process overview and scheduling

Every time step, the model runs in a predefined order (Figure 1). First, a defined number of land parcels representing the households are placed randomly in space. Model then calculates cultivable area and food production for each household. Households with adequate food supply are identified as food secure. Households with food shortages look for options to secure food for the family.

get_cultivable_area: The model first estimates cultivable area of each household. Since farming is predominantly manual, depending upon the farm workers at home, cultivable land may be smaller than total farmland. Famers have one crop cycle a year; they divide the cultivable area for maize, millet, and sorghum cultivation.

get_status: Once the ABM calculates household food production, it converts the available food to calorie supply and checks for its sufficiency. Households with positive calorie sufficiency (calorie sufficiency = calorie supply – calorie demand) are tagged as food secure (FSVI I) households.

get_inkind: Food insecure households seek for in-kind support from their neighbors. Every household is provided with a predefined neighborhood size. Neighbors with surplus food contribute a small portion from their food storage.

use_cattle: Households with more severe food shortages sell cattle to buy food. However, households do not sell all their livestock as they need some for farming.

off_farm: Households also send some family members to off-farm jobs to be able to purchase food. Some members decide to migrate that creates labor shortages at home. As households do

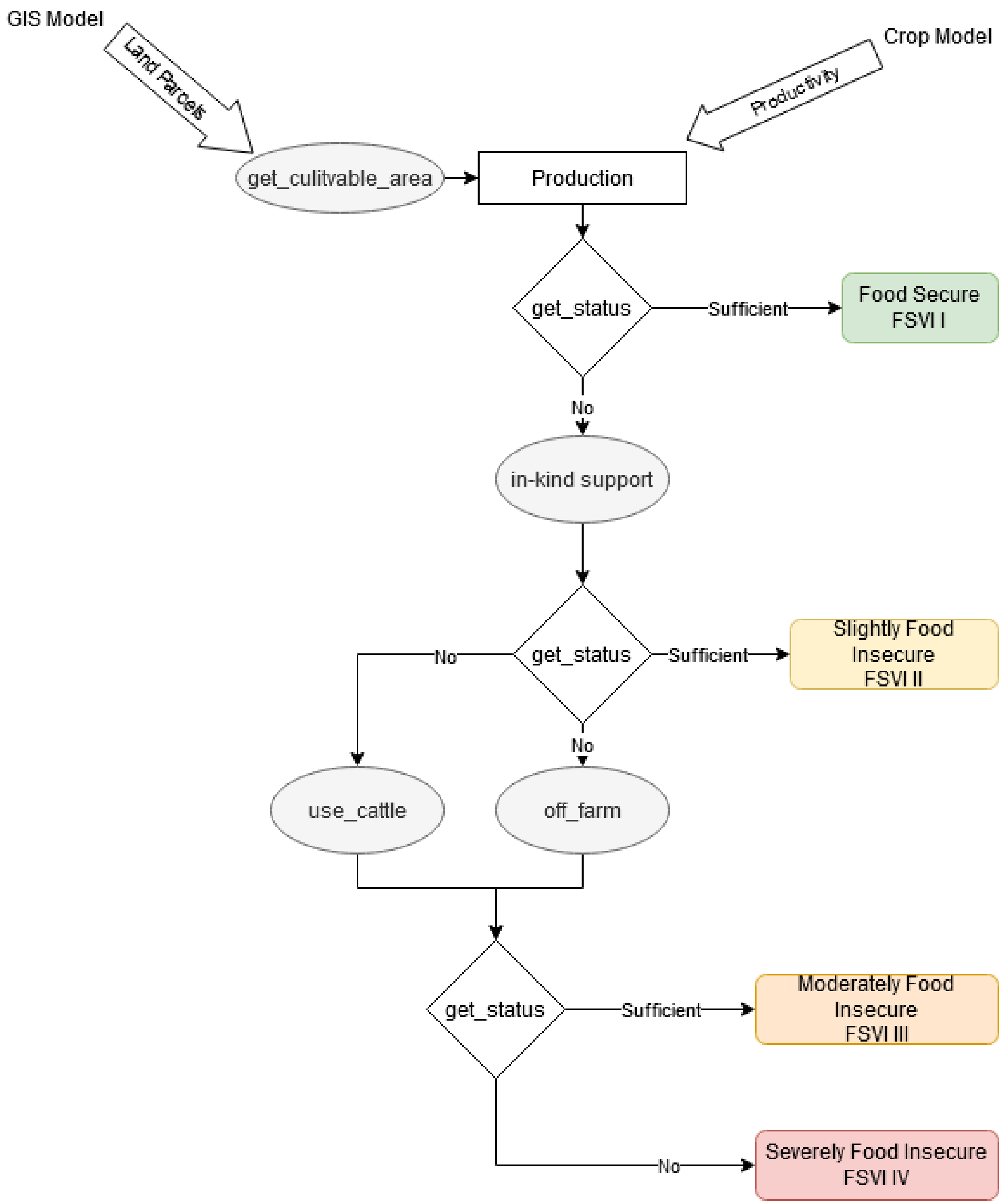

Figure E.1: ABM flow diagram

not want to lose their farm workers, off-farm job is used as the last available option.

E.4 Design concept

Basic principles: Vulnerability is defined by exposure to risk, capacity to cope, and ability to recover (Watts and Bohle 1993). Households starts to cope when faced with food shortages. Coping mechanisms usually start with high accessible low impact options. Households gradually move to low accessible high impact options as severity of food shortages increases. Such options may hinder households capacity to cope in the future. The ABM checks household food sufficiency, looks for available coping options and measures the vulnerability based on the recovery potential.

Emergence: The spatial and temporal distribution of household vulnerability to food insecurity is an emergent phenomenon that results from households' interactions with each other and their environment.

Adaptation: During food shortages, households first start with low-impact coping options like skipping or rationing meals and getting in-kind help from relatives and neighbors, and slowly move to high-impact alternatives.

Objectives: The overall objective of the households is to secure enough food for the family without impairing their ability to fight future vulnerabilities.

Interaction: Households interact with each other and the environment. Environment (i.e., crop productivity) influences household food sufficiency that affects household behavior. Households interact with other households for food (for in-kind support). Households also go for off-farm jobs and to market to buy food or sell livestock.

Stochasticity: Stochasticity is incorporated at various places in the model. First, the land parcels' shape, size, and the distribution over the landscape are random. Additionally, the model populates agents' attributes from the predefined probability distribution (Table 1).

Observation: The model measures household vulnerability to food insecurity using Food Security Vulnerability Index (FSVI). Households with FSVI I are self-sufficient and food secure. FSVI II households face slight food shortages that can be addressed through meal rationing or in-kind help. FSVI III households need to purchase food. They might need to go for off-farm jobs or sell their livestock to be able to purchase food. FSVI IV households neither have sufficient food production nor they have resources to purchase food. The model shows the temporal distribution of household vulnerability to food insecurity. Since this is coupled with a process-based crop model, we also see the impacts of climate change on household food production and security. Additionally, as the model is spatial in nature, we can also see the distribution of household vulnerabilities across space.

E.5 Initialization

The model consists of 9000 agents, amongst them 1170 are HRE_LH, 2520 are HRE, 1710 are LRE, and 3600 are MRE. Land parcels representing the agents are randomly placed within the cultivable area of the landscape. We use 'Thiessen Polygon' feature in ArcGIS to generate the distributions of land parcels. We have above 2000 realizations of GIS model and ABM picks one land parcel distribution (at random) at the start of a run. ABM divides households' cultivable areas to parcels for maize (20%), millet (40%), and sorghum (40%). The model receives productivity information from the crop model. Other attributes are populated from the provided distribution (Table 2).

Table E.2: SALUS Parameters

SALUS Parameterization			Source
Soil	**Parameters**	**Resolution**	International Soil Reference and Information Center (`http://www.isric.org`)
Physical Properties	Bulk density, Clay content, Coarse fragments, Sand, Silt	250m	
Chemical Properties	Cation exchange capacity, Nitrogen, Soil Organic Carbon, pH	250m	
Weather/Climate	**Parameters**	**Resolution**	Marksim DSSAT weather file generator (`http://gismap.ciat.cgiar.org/MarkSimGCM`)
Weather data	Tmax, Tmin, Rainfall, Solar radiation	Daily	
Future Climate	RCP 8.5 (HadGEM2-ES)	-	
Farm Management	**Parameters**	**Value**	Focus Group Discussion/ Expert Advice/ (Soumaré et al. 2002)
Crops	Maize, Millet, Sorghum	20%, 40%, 40% of total land respectively	
Input	Barnyard Compost	1T/ha	

Table E.3: ABM Parameters

ABM Parameterization					Source
Total Farm Households (No of Agents)		9000			Census (2009)
HH typologies	**Distribution**	**Land_size: mean (std)**	**HH_Size: mean (std)**	**Livestk: mean (std)**	(Falconnier et al. 2015)
High Resource Endowed - Large Herdsize (HRE_LH)	13%	16.6 (8.33)	45.3 (18)	5.7 (1.5)	
High Resource Endowed (HRE)	28%	11.8 (6)	27.3 (6.6)	2.7 (1.6)	
Medium Resource Endowed (MRE)	40%	7.5 (2.4)	12.6 (1.7)	4.1 (6.5)	
Low Resource Endowed (LRE)	19%	3.2 (2)	7.9 (4.9)	1.3 (1)	
Food supply	**Values**				
Calorie demand	2400 per person				FAO (http://www.fao.org/)
Calorie supply	3100 per kg maize; 3550 per kg sorghum/millet				
Sale of 1 cattle provides	1285 kg of grain				Derived from ICRISAT, 2017
Food Production	**Values**				
Workforce available	1/2*hh_size				(Ruben et al. 1997)
Worker-days required (Crops)	63				
Worker-days required (Cotton)	149				
Food Access	**Distribution**				
Neighborhood distance	Uniform 2000,3000,4000 (meters)				based on Focus Group Discussion
Neighborhood support	Discrete (0%, 5%, 10%, 20%) % of surplus	P(0.1,0.5,0.3,0.1)			

E.6 Input data

The ABM is coupled with SALUS - a process-based crop model. SALUS requires soil, climate crop, and farm management information to predict crop productivity (Basso, Ritchie, et al. 2006). SALUS is provided with information on soil biophysical and chemical properties, climate, and farm management. Additionally, we use RCP 8.5 to represent future climate scenario. Farm information is obtained from focus group discussions in the field. SALUS provides estimated crop productivity for each land parcel for every year until 2050.

E.7 Submodels

get_cultivable_area: Since households are essentially into manual farming, available farm labor at home determines the areas that a household can cultivate . According to Ruben et al. (1997), only ½ of household members can be considered as farm labors. They also suggest that cultivating 1 ha of cereal crop requires 63 man-days in the region. Assuming a farm labor can work for 120 days (a crop season) per year, we estimate cultivable_area of the household by: Man-days available = ½ household * 120 Man-days required = 63 cultivable_area = man-days available/man-days required

get_status: This simply calculates household food sufficiency. Households with positive caloric sufficiency (calorie sufficiency = calorie supply – calorie demand) are categorized as food sufficient.

get_inkind: Households with food shortages initially try low-impact options for securing food. If a household has a low food shortage (less than 5% of total food demand), it skips/rations to address the problem. However, if it suffers from larger food shortages, it seeks for in-kind help from neighbors or relatives. Every household has defined a neighborhood area (walkable distance - ranging from 2 to 4 km). It looks for help from food secure households within the neighborhood area. Neighbors usually donate a small portion (0-20%) from their surplus food.

use_cattle: When neighbors' support is not enough, households buy food from market. Since most of the households are cash-constrained, they might have to sell their livestock to be able to purchase food. Every time step, a household sells one of their livestock (cattle) to purchase food. They will keep at least 2 livestock at home for farm work. Using ICRISAT data (Badolo 2017), we estimate the average price of 1 kg crop (140 FCFA) and unit price for adult cattle (180,000 FCFA). Using the information, we estimate the amount of food that can be purchased by selling one cattle. We also assume a uniform inflation across commodities in the future (i.e., prices for cattle and food increases/decreases at the same rates).

off_farm: In addition to sale of livestock, households also send their members for off-farm jobs. We assume that the off-farm jobs result in food sufficiency at home. However, based on the focus group discussion, we learned that around 15% of members going for off-farm jobs do not return. Such out-migration results in lower food demand, but also decreases farm labor at home.

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CHAPTER 4

GLOBAL OR LOCAL? EFFECTS OF POLICY INTERVENTIONS ON HOUSEHOLD FOOD SECURITY IN KOUTIALA, SOUTHERN MALI: A COUPLED BIOPHYSICAL AND SOCIAL SYSTEMS APPROACH.

Northern Mali is highly arid and not suitable for agriculture. The South is mainly responsible for supplying food to the nation. However, climate change and rapid population growth in the South are threatening local food production and food security. Regional food demand is likely to surpass its production very soon. Besides, the majority of households in the South are likely to be food insecure in the near future. This can tremendously affect the national food supply. The South needs to act soon to maintain its food security and the food supply to the nation. In this study, we evaluate the effectiveness of global and local level interventions in addressing household food security in the region. We integrate a biophysical process-based crop model with an agent-based model of household food systems to explore the trajectories of household food security under policy interventions. We find that the local level interventions that include improved access to agriculture inputs and reduced population growth are highly effective in promoting household food security in the region. At least 60% of the households could remain food secure by mid-century under the local level interventions. On the other hand, global level intervention that includes climate change mitigation to RCP4.5 levels does not show immediate effects on food production and food security in the region.

4.1 Introduction

Mali is expected to be profoundly impacted by climate change. Climate models used by the Intergovernmental Panel for Climate Change (IPCC) unanimously agree that the country will experience warmer weather in the future (Traore et al. 2013). High temperature shortens the plant's phenological cycle and reduces biomass accumulation (S. Asseng et al. 2017; Basso, Kendall, and Hyndman 2013) that can have a significant impact on regional crop production. Maize, millet, and sorghum are the major staple crops grown in the region. Since these crops are C4 plants, they are less likely to be affected by increased temperature (Roudier et al. 2011). However, every degree rise in temperature can decrease maize productivity by 0.5T/ha (Bassu et al. 2014). Yields of other C4 crops are also expected to decline under climate change (Schlenker and Lobell 2010; Sultan et al. 2013). Since productivity in the region is currently very low, further loss in yields could be detrimental to the regional food supply. Although Mali may see an increased rainfall in the future, its impact on crop production is expected to be marginal (Sivakumar 1988).

Northern Mali is highly arid and not suitable for agriculture. Being more productive, the South has the responsibility to feed the entire national population. Koutiala, our study area, lies in the South and receives 600-1400mm of rainfall annually (refer to Figure 1.1) (Falconnier et al. 2015). Farming is the prime activity here. Food grown locally gets exported to the North and other parts of the nation. Since the region plays a significant role in the national food supply, it is considered the breadbasket of Mali (Bingen 1998). However, with climate change, the region is expected to lose its productivity significantly. Our study in the previous paper finds that the mid-century maize and sorghum yields could fall by 40%. Additionally, with the current level of population growth, Koutiala is likely to see a massive surge in food insecure population in the future. Around 80% of the households will be at risk of food insecurity by 2050. Moreover, regional food demand is likely to surpass its food production by 2025. This could significantly impact food supply to the nation, potentially jeopardizing the breadbasket status of the region. Mali needs to act soon to promote food security in the region in order to maintain the national food supply.

Food security lies at the interface of biophysical, climatic, and socio-economic systems (Hammond and Dube 2012). Besides, household food security is determined by household food access and production. In this study, we couple a biophysical process-based crop model with an agent-based model (ABM) of household food systems to explore the trajectories of household food security in Koutiala. Using the coupled model, we test the efficiency of global and local level interventions in promoting food production and security in the region. The crop model integrates the dynamics of biophysical and climatic systems to simulate household food production, and the ABM explores prevailing socio-economic systems to evaluate household food access. The study has significant policy implications in that, it explores future trajectories of household food security and evaluates the efficacies of selected interventions.

The process-based crop and the agent-based models are systems models (J. W. Jones et al. 2017; Parker et al. 2003) and ideal tools for performing scenario analyses (Boero and Squazzoni 2005). Unlike the models based on statistical relationships, systems models capture the interplay within and across the associated dynamic systems (Basso and Liu 2019). Such complexity is essential for effective scenario analyses. ABM can simulate human decisions and interactions with great realism and, hence, has been widely used as a virtual laboratory for social experimentations (Ligmann-Zielinska and Jankowski 2007; Parker et al. 2003). It allows modelers to explore micro-level interactions responsible for macro events. Even simple ABMs can explain complex phenomena (Epstein 2006). Conway's Game of Life and Shelling's Segregation are prime examples of simple models explaining the emergence of macro-phenomena from micro-interactions (Axelrod 1997). Complex and more realistic ABMs need empirically-based sophisticated algorithms for decision and interaction. These models allow modelers to explore complex systems, perform modifications, and evaluate alternative outcomes.

Farm field experimentations may not always be feasible due to spatio-temporal and economic limitations. Crop models provide cost-effective, practical, and efficient options to carry out agricultural investigations (J. W. Jones et al. 2017). Process-based crop models have interconnected modules containing a series of mathematical equations representing crop growth, soil nutrient cycling, soil water balance, and temperature (Basso, Ritchie, et al. 2006). As the changes in one module are reflected in others, these models allow researchers to evaluate the implications of modification in one system on others. Such analyses allow farmers and policymakers to identify sustainable and effective management options (Basso and Ritchie 2015). For example, Basso, Sartori, et al. (2012), and Liu and Basso (2017) used crop models to evaluate changes in Nitrogen application on crop production and environment. S. Asseng et al. (2017) used multiple crop models to check the effects of changes in atmospheric temperature on wheat yield. Similarly, Basso, Ritchie, et al. (2006) used a process-based crop model to evaluate the effects of tillage differences on soil conditions and crop yields. García-Vila and Fereres (2012), on the other hand, used a crop model, in combination with an economic model, to evaluate sustainable water management at the farm level.

The coupled model has added advantages over the decoupled crop and agent-based models. Crop models do not consider the social side of farming and crop production (Antle et al. 2017; James W Jones et al. 2017). Similarly, ABMs cannot incorporate crop growth and dynamics. Our integrated model adds crop dynamics to the representation of a social system. This allows modelers to explore human interactions and their implications on farming and crop production. Literature contains only a few examples integrating crop models with ABM for analyzing the effects of farm management on household food production (Wossen and Berger 2015), economy (Schreinemachers and Berger 2011; Schreinemachers, Berger, and Aune 2007), and environmental management (Marohn et al. 2013). Crop modelers are increasingly aware of such limitations demanding more integration with social systems (James W Jones et al. 2017).

4.2 The coupled model

We develop the ABM of household food systems using information from field interviews and focus group discussions. The field interviews are useful for developing the ABM structure, while the focus group discussions help us formulate decision making in the model. Agents in the ABM represent farm households from Koutiala. We have 9000 agents in the models represented in the landscape by their land parcels. We develop a GIS model to generate distributions of land parcels as vector polygons of different shapes and sizes. Since the agents are farmers, the land parcels are placed in arable land. Additionally, land parcels are smaller and densely distributed in and around urban areas reflecting their actual spatial distribution (N'Danikou et al. 2017). Households are classified into the following four groups based on their land sizes (Falconnier et al. 2015):

1. High Resource Endowed – Large Herds (LRE_LH) households

2. High Resource Endowed (HRE) households

3. Medium Resource Endowed (MRE) households

4. Low Resource Endowed (LRE) households

We select the Systems Approach to Land Use Sustainability (SALUS) model as our crop model. SALUS is a process-based crop model that requires information on daily weather conditions, physical and chemical properties at each layer of soil, and information on farm management to simulate daily plant growth and development. Detailed information on SALUS can be found at https://basso.ees.msu.edu/salus/index.html. We use SALUS to simulate household cultivation of maize, millet, and sorghum in the region. The model structure, and SALUS and ABM parameters are presented in Figure 3.6 and Table 3.3 and Table 3.4 of Chapter 3, respectively. Additionally, we present detailed information on ABM in ODD format (V. Grimm et al. 2006; Volker Grimm et al. 2010) in Appendix E.

At the beginning of a model run, the ABM randomly selects a set of land parcel distributions generated by the GIS model. It then receives crop productivity from SALUS and interpolates the values to land parcels. ABM calculates household food sufficiency based on food production and household food demand. We develop a Food Security Vulnerability Index (FSVI) to measure household food security. FSVI is a coping-based vulnerability index that measures the severity of food security based on applied coping mechanisms by the households. Households generally use different coping mechanisms when faced with food scarcity. Such mechanisms range from low impact alternatives such as meal rationing or neighborhood support to high impact alternatives like sale of household assets, off-farm jobs, and migration. Their application reflects the severity of households' food scarcity and their future vulnerability (D. Maxwell, Caldwell, and Langworthy 2008; D. G. Maxwell 1996; D. Maxwell, Watkins, et al. 2003). The FSVI has four severity levels (Table 3.1).

4.3 Scenario analysis

Farmers in the region increasingly worry about low soil fertility and crop productivity (Olabisi et al. 2018; Rivers III et al. 2017). Poor access to input and farm management are major factors responsible for productivity decline. Farmers are also concerned about sporadic rainfall in the region (Rivers III et al. 2017). Climate change was one of the significant issues local farmers raised during our focus group discussions. Besides, the rapidly growing population is increasing regional food demand. Farmers demand a future where they have increased access to input and water availability for increased food production (Olabisi et al. 2018) to feed their household population. Based on farmers' concerns and observed issues in the region, we develop the following three interventions grouped by their spatial scale.

4.3.1 Intervention at the global level

4.3.1.1 Climate change mitigation (CCM)

Since Mali is likely to be profoundly affected by climate change, it is an essential issue for regional food security and food production. As seen in the previous paper (Figure 3.7), under Representative Concentration Pathway (RCP) 8.5, the mid-century temperature could rise by 2°C. That can have detrimental impacts on regional food production. Although future rainfall largely remains the same, the increased temperature can in turn increase evapotranspiration that can exacerbate the regional water problem. Malian alone cannot contribute to climate change mitigation as it requires a global effort. With the realization that climate change is currently unavoidable, we consider a less severe climate change, i.e., RCP 4.5, under which, emission of greenhouse gases is curbed. This can positively contribute to regional food production by lowering the temperature and its resulting evapotranspiration.

4.3.2 Interventions at the local level

4.3.2.1 Lower population growth (LPG)

Population growth rate in Koutiala, currently at 5% per annum, is higher than the national average. Households in the region are usually big, containing extended family living together and working in collective farms (Rivers III et al. 2017). Since farming is mainly manual, large households are generally preferred. For locals, a large family means more people to work in the field and go for off-farm jobs. Remittances from off-farm jobs generally support household food purchases (Eozenou, Madani, and Swinkels 2013; Rivers III et al. 2017). Since the large family is considered beneficial, population growth is often a non-issue here. However, the increase in population increases food demand, and for food constrained households having a large family might not always be beneficial. On the other hand, small families have a small agricultural workforce that can negatively impact household food production. It is crucial to explore the tradeoffs of population growth on household food production and demand. For this scenario, we set the population growth equal to the national average of 3% per annum.

4.3.2.2 Improved access to agricultural inputs

Koutiala has a large cotton industry that provides logistic supports in the form of credits, training, and agricultural inputs to cotton farmers in the region. The technologies and inputs used for cotton also help with crop production. Hence, to become its beneficiaries, most of the households in the region choose cotton production (Dembele et al. 2017). Households allocate a small portion of their farms for cotton plantation. However, support from the cotton industry is not usually sufficient for the entire farms. Since most of the farmers are food poor, they severely lack resources to purchase agricultural input. Households usually prepare manure using household and farm residues, but its application is often insufficient (Traore et al. 2013).

Under this scenario, we increase the application of input and check its impact on household food production and food security. We test the following two sub-scenarios:

- *Mixed access to input (MAI)*: Since resourceful households usually have better access to inputs than resource-scarce households, HRE_LH and HRE households apply 5T/ha of manure in their fields. In contrast, households with low endowments (i.e., MRE and LRE households) apply 1T/ha.
- *High access to input (HAI)*: All households have high access to inputs; all apply 5T/ha of

Table 4.1: Combinations of intervention scenarios

Scenario ID	**Assumptions**	**Access to Input**	**Climate Change**	**Population Growth**
BAU	Business-as-usual	Low (1T/ha)	RCP8.5	5%
CCM	Climate Change Mitigation	Low (1T/ha)	RCP4.5	5%
HAI	High Access to Input	High (5T/ha)	RCP8.5	5%
LPG	Low Population Growth	Low (1T/ha)	RCP8.5	3%
CCM+LPG	Climate Change Mitigation + Low Population Growth	Low (1T/ha)	RCP4.5	3%
HAI+CCM	High Access to Input + Climate Change Mitigation	High (5T/ha)	RCP4.5	5%
HAI+CCM+LPG	High Access to Input + Climate Change Mitigation + Low Population Growth	High (5T/ha)	RCP4.5	3%
HAI+LPG	High Access to Input + Low Population Growth	High (1T/ha)	RCP8.5	3%
MAI	Mixed Access to Input	Mixed (5T/ha, 1T/ha)	RCP8.5	5%
MAI+CCM	Mixed Access to Input + Climate Change Mitigation	Mixed (5T/ha, 1T/ha)	RCP4.5	5%
MAI+LPG	Mixed Access to Input + Low Population Growth	Mixed (5T/ha, 1T/ha)	RCP8.5	3%
MAI+CCM+LPG	Mixed Access to Input + Climate Change Mitigation + Low Population Growth	Mixed (5T/ha, 1T/ha)	RCP4.5	3%

manure in their fields.

4.4 Results and discussion

In paper 2, we simulated a business-as-usual (BAU) scenario using high emission climate change (RCP 8.5), low access to input (1T/ha) and high population growth rate (5%). In this study, we ran multiple simulations for different combinations of scenarios (Table 1) and evaluated their impacts on household food production and security. Each simulation was run for 40 years (from 2010 to 2050) with a one-year timestep. For each scenario, we ran 50 simulations. We used High Performance Computing (HPC) at Michigan State University for the simulations. In this section, we present only the significant outputs of the above scenarios.

4.4.1 Intervention at global level

4.4.1.1 Climate change mitigation

The future climate under this scenario is highly similar to that of BAU (Figure 4.1). Although there are visible interannual variabilities, the overall rainfall pattern remains the same. However, the rise in temperature is lower under the RCP 4.5 climate change scenario. Since high temperature is detrimental to crop productivity, we expected to see an increase in yields under milder RCP 4.5 climate. Surprisingly, the crop model did not show significant variations in crop yields (Figure 4.2). In addition to the lower temperature, RCP 4.5 has lower ambient CO_2. CO_2 in the atmosphere acts as a natural fertilizer (Senthold Asseng et al. 2013) and plays a significant role in crop productivity, especially in dry climates (Asseng et al. 2004). Additionally, the increased level of ambient CO_2 reduces evapotranspiration (Asseng et al. 2004). Hence, we believe that the lower level of CO_2 under CCM largely neutralizes the benefits of lower temperatures in the atmosphere. Since the productivity did not change, household food security under CCM (Figure 4.3:1b) remained similar to that of BAU (Figure 4.3:1d).

4.4.2 Interventions at local/regional levels

4.4.2.1 Lower Population Growth

The coupled model showed a significant impact of LPG on household food security. Compared to BAU, which had a 5% annual population growth, the LPG intervention increased mid-century food security by 40% (Figure 4.3: 1c). Also, the severity of food security was reduced - the number of moderately food insecure (FSVI III) households significantly declined under this intervention. FSVI III households either became food secure (FSVI I) or slightly food insecure (FSVI II). We expected to see the impact of decreased farm labor under lower population growth on household food production and food security. However, the model suggested that such impacts were miniscule.

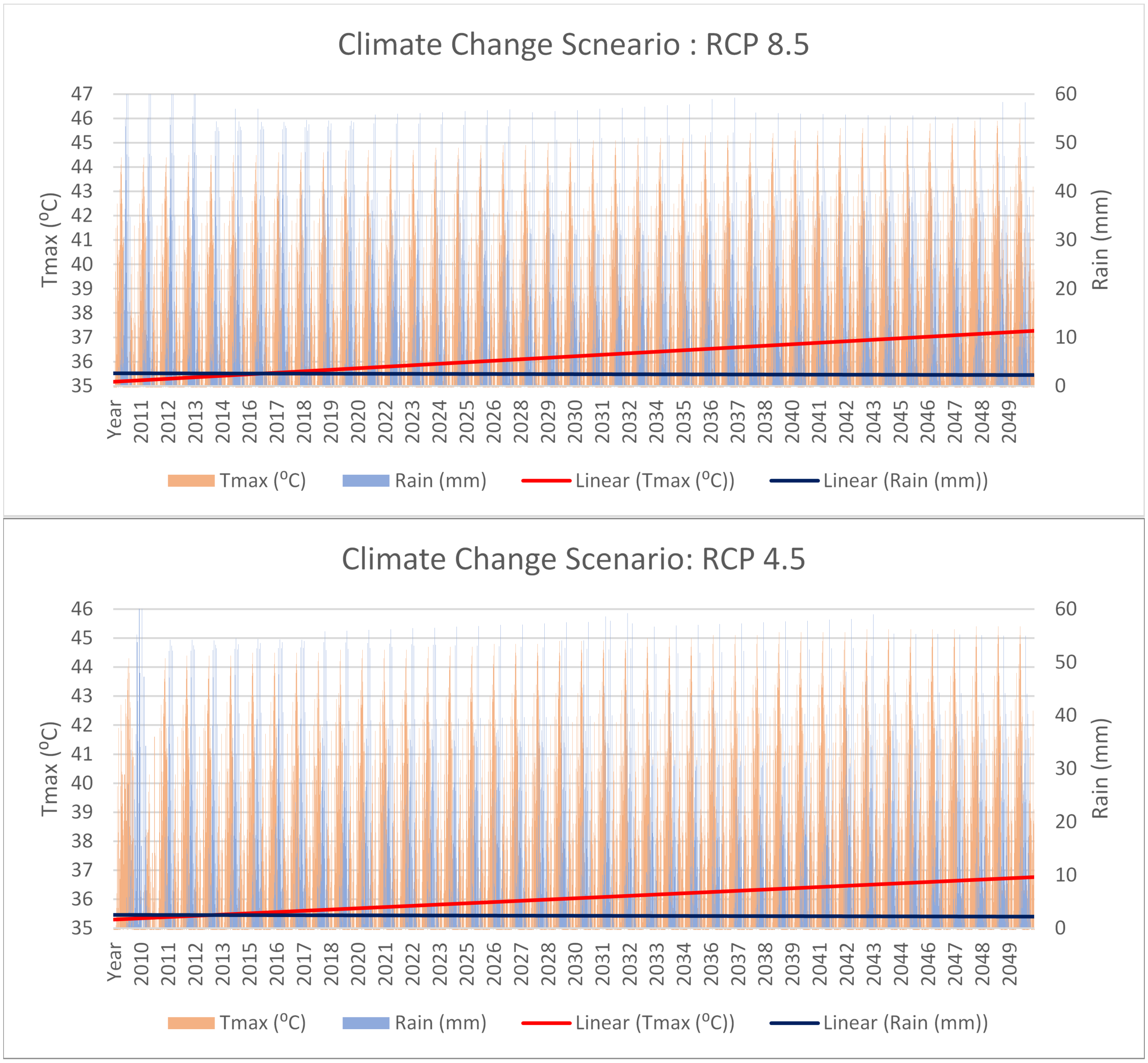

Figure 4.1: Climate predictions under BAU (RCP 8.5) and CCM (RCP 4.5) (RCP: Representative Concentration Pathway)

4.4.2.2 Improved access to agricultural inputs

Crop productivity increased substantially with increased application of inputs (Figure 4.4). That contributed positively to household food security in the region. Under the MAI scenario, mid-century food security rose to almost 40% (Figure 4.3:3d) compared to 20% in BAU. Under this scenario, only large endowed households (i.e., HRE_LH and HRE households), that constitute 40% of total farm households in Koutiala, have increased access to inputs. However, when all the households get equal and high access to inputs (HAI), there was a drastic improvement in household food security. More than 55% of the households would be food secure by 2050 under this scenario(Figure 4.3: 2d).

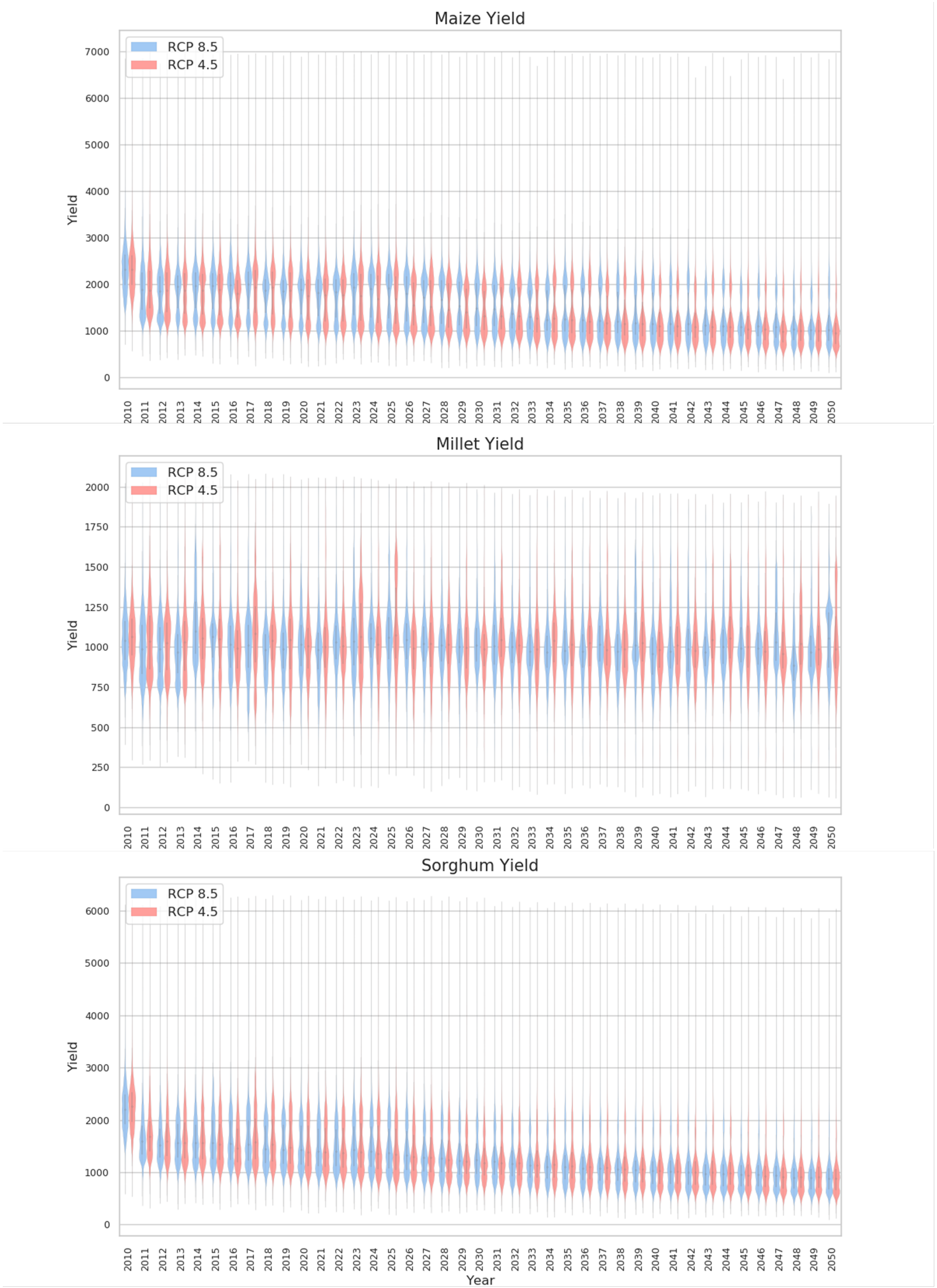

Figure 4.2: Crop yield (Kg/ha) under BAU (RCP 8.5) and CCM (RCP 4.5)

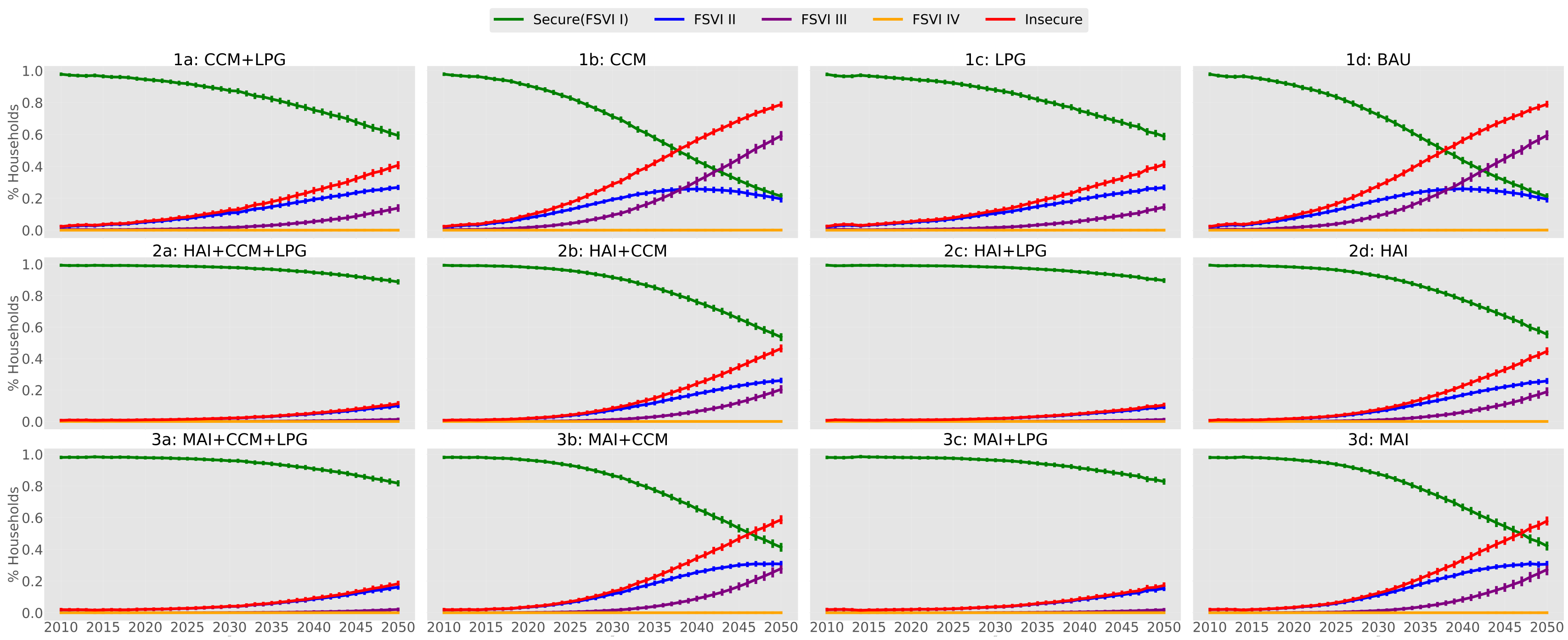

Figure 4.3: Household food security under different scenarios (LPG: Lower Population Growth, CCM: Climate Change Mitigation, HAI: High Access to Input, MAI: Mixed Access to Input)

In sum, the intervention at the global level was not effective in promoting mid-century household food security. However, trajectories of crop yields under RCP 4.5 and RCP8.5 are expected to change significantly beyond 2050 (Levis et al. 2018). This can have a very different impact on household food security in the region. Note that analysis beyond 2050 is not included in our study.

Both local level interventions are highly effective in addressing future food insecurity. However, different interventions affect households differently. Although LPG and HAI were equally effective, LPG has a slight edge in reducing the severity of food security, especially of smaller households (Figure 4.5). A combination of interventions that includes improved access to input and lower population growth, can significantly increase future food security. When HAI and LPG are combined, mid-century household food security can increase by up to 90%. Such an increase in regional food security can have significant impacts on local and national food supply.

The region contains many mildly food insecure (FSVI II) households. These households are supported by formal and informal cooperation between local community members. Households with surplus food generally support neighbors that are in need. Koutiala has various groups and cooperatives that promote supports amongst community members. They usually act as social safety-nets that absorb the impacts of food scarcity in the locality. They allow sharing of benefits amongst the community members. The impact of such cooperation is clearly visible in the MAI scenario. Although households having low endowment could not access high inputs, they could still reduce their food insecurity by 20% (Figure 4.5). These smaller households benefited from the improved production in their neighborhood, especially in large endowed households.

4.5 Limitations

The empirical results reported above should be considered in light of several limitations.

There are inter and intra-model variabilities in climate change projections. Crop models are highly sensitive to climatic parameters (Senthold Asseng et al. 2013). However, for the sake of simplicity and parsimony, we used only one observation from one climate model.

Furthermore, due to the loose coupling between the crop and the agent-based models, we

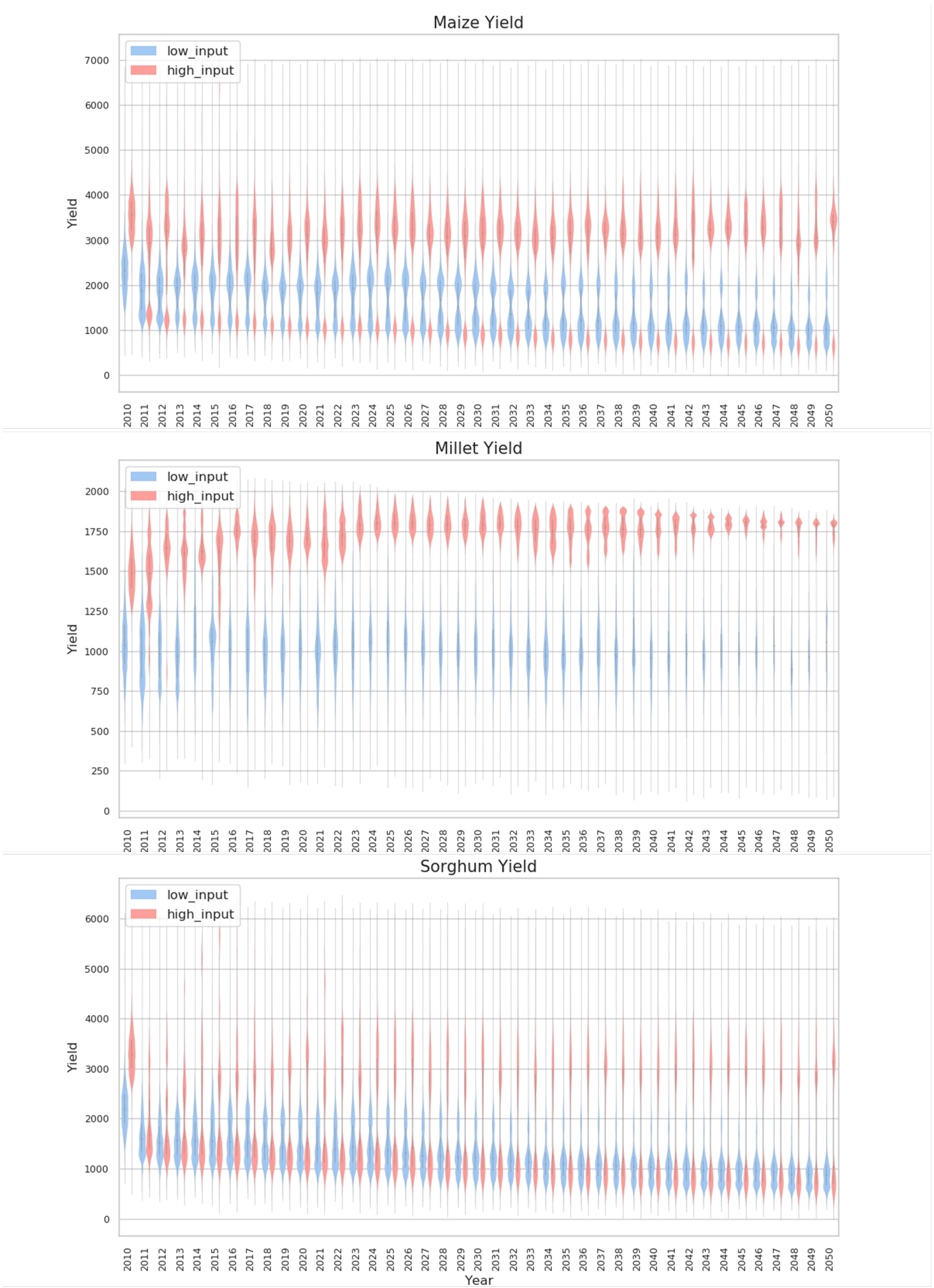

Figure 4.4: Crop yield (Kg/ha) under low and high access to input

assumed a uniform farm management across time and space. We also did not include learning and adaptation in the model. Such limitations could have resulted in overprediction of the food insecure households. Farmers regularly modify their farming practices; they apply improved technologies and crop varieties improving crop productivity and food security. Furthermore, resource availability may affect population growth. A constant population growth, assumed in the study, may not be possible under household food scarcity.

A desire for large households is engraved in the local culture due to their apparent benefits on farm and off-farm jobs. This raises a question of practicality of low population growth interventions in the local context. Consequently, the feasibility of improved and uniform access to agricultural inputs for all farm households in a developing country like Mali requires further study.

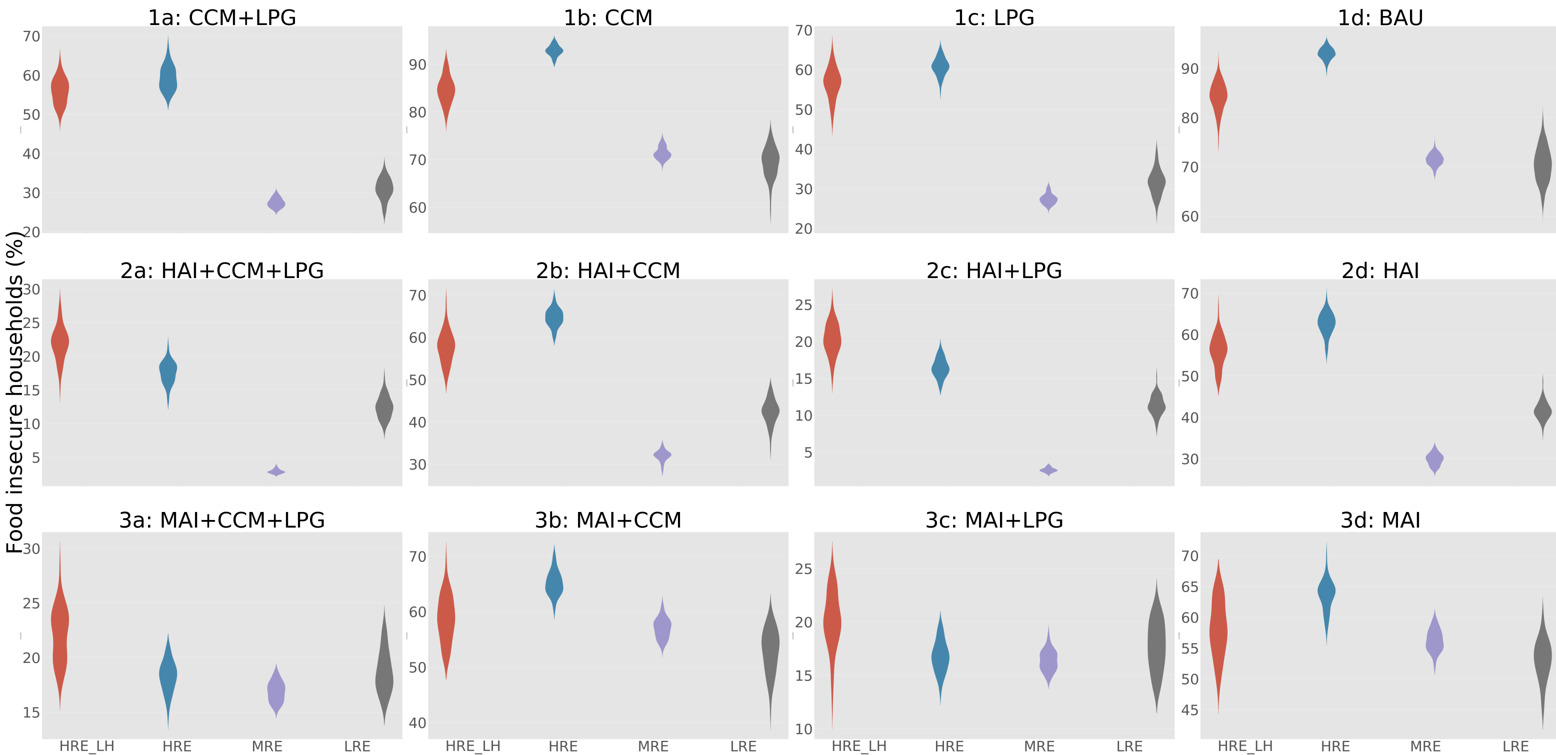

Figure 4.5: Food insecurity by household types

4.6 Conclusion

As northern Mali is unsuitable for agricultural farming, the South has the responsibility to feed the nation. So far, it has been able to export local production to other regions. Since Mali is expected to be impacted by climate change, its crop productivity is likely to decline. Moreover, the South is observing a rapid increase in its population. Local food demand will rise while the production declines. As a result, future without interventions could lead to massive food insecurity in the region.

Southern Mali has a daunting task of providing food to the locals while maintaining food supply to the nation. There is an urgency to start interventions to promote food security in the region. Based on our simulations, we conclude that local level interventions, such as improving farmers' access to input and controlling population growth, are effective in promoting household food security. In contrast, the global intervention that includes climate change mitigation to the RCP4.5 level does not have similar success in maintaining food production and food security in the region.

The coupled model incorporates the dynamics within and across biophysical, climatic, and social systems. As food security lies at the intersection of these systems, the coupled model is an appropriate tool for its analysis. Moreover, the interconnectedness between biophysical and social systems allows for exploring the impacts of changes in one system on others. Such characteristic is essential for evaluating policy interventions. Using the coupled model for scenario analyses has broader policy implications as it provides valuable information on the potential efficacies of the interventions in the modeled system.

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CHAPTER 5

CONCLUDING REMARKS

Koutiala, a region in the South of Mali, is currently considered the breadbasket of the country. The trajectories of national food supply depend heavily on food production and food security in Koutiala. **In this study, we analyzed the vulnerability of households to food insecurity in Koutiala**. Mali is expected to be profoundly impacted by climate change. Under a high emission climate change scenario, which is very likely without a global intervention, its mid-century temperature could rise by 2°C. This can have detrimental impacts on national crop production. Furthermore, southern Mali is mainly responsible for providing food to the nation as the North is highly unsuitable for agriculture. However, farming in the South has its own set of problems. Poor access to inputs and farm management has substantially lowered crop productivity in the region. With climate change, the region may see a further decline in its agricultural productivity. Moreover, Mali is experiencing rapid population growth. With reduced production, the country will struggle to feed its growing population.

Food security crisscrosses biophysical, climatic, and socio-economic systems. Household food security, particularly in rural areas, depends on household food production and access. We used a systems approach for defining and analyzing household food security and employed multidisciplinary tools to capture the dynamics of associated systems. Through combining an ABM, a model of the social system that analyzes social interactions for food access, with a biophysical crop model simulating crop production, we essentially captured the basic dynamics responsible for household food security. We used Food Security Vulnerability Index (FSVI), a coping-based index, to measure vulnerability to future food insecurity at the household level. Furthermore, we incorporated all four dimensions of household food security in our analysis. Household food **production** was used to obtain information on food availability. We assessed household food **access** by analyzing resource availability and social interactions. Similarly, calorie sufficiency was used to estimate household food **utilization**, and temporal **stability** was represented through simulations.

Agent-based model development needs information on systems actors and their interactions. **In chapter two**, we aimed to identify actors (agents) of household food security in Koutiala, together with their characteristics, and their interactions required for the development of agent-based model (ABM). Since qualitative data, especially in the narrative form, contains rich contextual systems information, we decided to use field narratives to extract ABM components. Qualitative data extraction is usually tricky and often blamed for being subjective and bias-prone. Modelers often skip extracting model components from narratives and develop models based on their subjective interpretation of the target systems. This can produce models with questionable credibility. In this chapter, we used Natural Language Processing (NLP) tools for enhancing and expediting qualitative data extraction for model development. Using a combination of semantic and syntactic tools, we used an unsupervised approach to extract information on agents and their attributes and interactions. We identified subjects of sentences as agents, while root verbs were characterized as actions. Similarly, we obtained attribute information from sentences containing possessive nouns and be or have as their root verbs. We contextualized the extracted information manually and asked the stakeholders for evaluation. Since the approach is mainly unsupervised, especially during the initial information extraction, it controls opportunities for subjectivity and biases during model development.

In chapter three, we explored the future trajectory of household food security in Koutiala. We developed an ABM of household food security and integrated it with (Systems Approach to Land Use Sustainability) SALUS, a process-based biophysical crop model. Using the crop model, we simulated household cultivation of maize, millet, and sorghum – the three major cereal crops in the region. For the simulations, we defined a 'business-as-usual' scenario based on the current state of regional farm management, population growth, and global climate change. The ABM received productivity information from SALUS and calculated household food availability and demand. Households with sufficient food were tagged as food secure. We simulated the interactions for food access by food-deprived households and provided FSVI values to the households based on their interactions. Under status-quo, the model predicted a massive reduction in crop productivity;

maize and sorghum productivity, in particular, could decline by almost 40%. We also found that almost 80% of the Koutiala population is likely to be food insecure by 2050. Large households are particularly vulnerable to food insecurity, and smaller houses are more likely to suffer from severe forms of food insecurity.

A staggering level of food insecurity in one of the most productive regions of the nation is troublesome. Mali needs to start promoting food production and food security in the South. **In chapter four**, we formulated three global and local level interventions based on observed issues and local public demand. We simulated climate change mitigation to the RCP4.5 level as a global level intervention. For the local level, we formulated scenarios with low population growth and a high level of input application. The consequences of climate change mitigation appeared to be highly similar to the Business-as-usual scenario. Even though the intervention represents lower temperature, its benefits on regional food production and food security were noninfluential. We believe that the lower level of atmospheric CO_2, predicted under RCP4.5, canceled the expected benefits of a lower temperature. As a result, household food security would remain unaffected under the global level intervention, at least until 2050. However, both local level interventions were highly effective in showing immediate impacts on household food security in the region. More than 60% of the households in Koutiala are likely to remain food secure under any of the local interventions. Besides, a combination of the local level interventions could substantially increase food secure households, which can significantly promote food supply to the nation.

In sum, Mali relies on the South for food, and it needs to act soon to maintain the food supply to the nation. Without any interventions, the majority of households in the South will soon be food insecure potentially disrupting the national food supply. Our simulations suggest that Mali should immediately focus on local level interventions to promote regional food security and national food supply.

There are five major technical and methodological limitations in this study to be addressed in future research. First, we only extracted individual sentences during NLP data extraction, which resulted in increased ambiguity and loss of contextual information. We encourage extracting a set containing sentences before and after the sentence identified for extraction. This can help preserve contextual information and reduce ambiguity. Additionally, extracting a set instead of individual sentences can help resolving pronouns used in the sentences. Second, the NLP data extraction was largely limited to syntactic analysis. We focused mainly on extracting agents, attributes, and interactions using syntactic approaches. Future research should increase the use of semantic analysis for understanding decision-making in the system. Compound and conditional sentences, we believe, could provide the key to decisions in the system. The third limitation is the failure to identify other actors of household food security. Since our data source contains information collected from household members, information on other actors of household food security was left out. This prompts for careful consideration of all candidate agents identified during the NLP analysis.

The fourth major shortcoming is related to the loose coupling between the ABM and the crop model. Due to models high resource requirements, we opted for a loose coupling between the models. This essentially prevented us from introducing some crucial dynamics in the analysis. Although the crop model captures the heterogeneity in weather and soil conditions, we kept the farm management uniform across time and space. Farmers learn from experience and make modifications in their farming approaches. Such adaptation could not be incorporated due to the loose coupling. A more integrated model can update farm management input to the crop model in real-time. The final limitation involves the exclusion of cash crops and non-farm incomes in model simulations. The regional farmers are involved in cash cropping and cottage industries, and their income helps in food purchases. Future research should include all types of income contributing to food security at the household level.

With all the limitations, the data extraction process is quick, structured, and effective. It can become a suitable substitute for lengthy and subjective traditional data extraction for model development. This can help ABM developers in identifying model components and interactions needed for credible and reliable model development. Similarly, the coupled model is highly useful for comprehensive household food security analysis. The model effectively integrates dynamics across multiple systems responsible for household food security. Besides, the coping-based index is simple and incorporates multiple dimensions of food security. Overall, the model we presented is an efficient and cost-effective laboratory for exploring expected and alternative futures of household food security for evaluating effective intervention strategies.