# Modelling decision making under risks; the case of smallholder farmers in Northern Ghana

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# Executive summary

Smallholder farmers in semi-arid West Africa face challenges of low soil fertility, and weak market infrastructure which limit their ability to invest in improved farming practices. Additionally, intra- and interannual weather variability is very high, which makes any investments very risky. In response to the resulting production and income shocks that can result from extreme weather or other factors, farmers often rely on temporary coping measures, such as selling farm and household assets and withdrawing children from school, resulting in long-term impoverishment. To break these poverty traps, there is a need for affordable and sustainable risk management approaches supporting farmers at the farm level. Proposed strategies in the literature include risk reduction using stress-resistant crop varieties, agroforestry, and conservation agriculture, among others. However, risk reduction often requires additional investments, risk transfer options like crop insurance and contract farming on the other hand require additional financial means. Despite experimentation with insurance products in sub-Saharan Africa, low adoption persists due to factors like high premiums, farmers' economic behaviour, and cognitive factors. To comprehensively manage risks on the farm, it is needed to combine several options that include risk reduction, risk transfer, savings and smart risk-taking as single options are not as likely to be effective under so many forms of risk and the concurrent need to improve productivity and livelihoods.

Modelling can support understanding the relationships between productivity, environmental, and economic aspects of crop production and inform crop management decisions about resource allocation and risk management options under different weather scenarios. However, few studies have investigated this considering the effects of weather variability on crop management and resource allocation. This thesis introduces an integrated bio-economic modelling approach to optimise resource allocation for smallholder mixed crop and livestock farming systems in Northern Ghana. Subsequently, the model is applied to assess the probability of two different index-based insurance products to stabilise smallholder Northern Ghana farmers' income and limit asset losses under a range of weather conditions. The effects of basis risk on the effectiveness of weather index-based insurance to increase income and reduce asset loss in Northern Ghana are further explored. The integrated model combines a process-based crop model, a farm simulation model, and an annual optimisation model. Large ensemble weather time series were used to drive the crop model simulations, which enables the exploration of a range of weather conditions for robust risk climate assessments. First, to evaluate the response of the model under different weather conditions, the large ensemble data was categorized into two weather scenarios: good and bad weather.

The model accounts for the effects of climate risks on-farm management decisions, which can help in supporting investments in sustainable intensification practices, thereby bringing smallholder farmers out of poverty traps. The model simulated three different farm types represented in the region based on their resource endowment. Data for the thesis was obtained from a household survey conducted by CGIAR CASCAID in 2020 and another in-depth survey carried out in 2022. In addition, secondary data was obtained from the Ministry of Agriculture Ghana (MoFA), the Ghana Statistical Service and ACRE Africa.

The results from the integrated model showed that the farm-optimised cropping patterns depend on the weather, as the model suggested more diversified cropping patterns that include the cultivation of both food and cash crops under bad weather conditions, while less diversified cropping patterns that comprise majorly of cash crops like soybeans, rice and groundnut was advised under good weather conditions. Furthermore, for the weather index-based insurance, insurance contracts were compared—one covering seeding costs and another addressing full input costs to the case of no insurance, as well as the role of replanting after crop establishment failure, for effects on crop allocation, incomes, and assets. The result indicated that farmers would be better off purchasing seed insurance that incentivises them to replant in the event of bad weather, stabilising their incomes and reducing the sale of their assets. These insurance options are relatively cheaper than full weather index insurance for the resource-constrained farmers considering that extreme weather conditions do not occur regularly. However, despite the usefulness of these insurance options, our results further highlight how poorly designed insurance contracts can be affected by basis risk, with product basis risk simulated by changing soil depth leading to the highest overpayment and underpayment of indemnities compared to the reference scenarios. This has led to suggestions that include designing insurance contracts by considering the farmers' economic and environmental conditions.

This thesis is significant for those designing risk management interventions for smallholder farmers in semi-arid West Africa, who are faced with economic and environmental challenges. Focusing on Northern Ghana, a region that is affected with high interannual weather variability, alternative risk management options that can help farmers to stabilise their income under adverse weather conditions were examined. By presenting the probability of outcomes for income and farm assets, particularly through seed insurance incentivizing replanting after extreme weather conditions, the thesis provides knowledge to better inform the design of insurance products, highlighting differential effects based on farmers' resource endowment and the type of product and extreme weather experienced. Here we see potential that the framework could be further developed to use in participatory settings with farmers to explore when the index product

leads to losses and in which cases it would provide benefit. The results also suggest the sources of basis risk which lead to the greatest error in estimated income and can be used to prioritise new data for improving index performance.

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## List of abbreviation

| | |
|---|---|
| ACRE | Agriculture and Climate Risk Enterprise Ltd. |
| ANDERS | Agricultural and Development Economics Model for the Groundnut Basin in Senegal |
| APNI | African Plant Nutrition Institute |
| BEFMs | Bio-economic farm models |
| BIC | Bayesian Information Criterion |
| CASCAID | Capacitating African Smallholders with Climate Advisories and Insurance Development |
| CCAFS | Climate Change, Agriculture and Food Security |
| CELSIUS | Cereal and Legume crops Simulator under changing Sahelian Environment |
| CGIAR | Consultative Group on International Agricultural Research |
| CLEM | Crop Livestock Enterprise Model |
| CSIR | Council of Scientific & Industrial Research |
| CSIRO | Commonwealth Scientific and Industrial Research Organization |
| EPIC | Environmental Policy Integrated Climate |
| FAMD | Factor analysis on mixed data |
| FAO | Food and Agriculture Organization |
| FC | Flowering drought cover |
| FSSIM | Farm System Simulator |
| FSSIM-Dev | Food Policy Impact at Farm-household Level in Developing Countries |
| GAIP | Ghana Agricultural Insurance Pool |
| GAMS | General Algebraic Modelling System |
| GC | germination drought cover |
| GHS | Ghana Cedes |
| GIEWS | Global Information and Early Warning System |
| GM | Gross margin |
| HAPPI | Half a degree additional warming, prognosis, and projected impacts |
| HPAD | Historical payoffs average data |
| HRE | High-resource-endowed farms |
| IAT | Integrated Analysis Tool |
| IPCC | Intergovernmental Panel on Climate Change |

| | |
|---|---|
| LRE | Low-resource-endowed farms |
| MoFA | Ministry of Agriculture Ghana |
| MOTAD | Minimisation of total absolute deviations |
| MRE | Medium-resource-endowed farms |
| PCA | Principal Component Analysis |
| PD | Planting date |
| PD-14 | Planting date minus 14 days |
| PD+7 | Planting date plus 7 days |
| PD+21 | Planting date plus 21 days |
| PMP | Positive Mathematical Programming |
| PPT | Precipitation |
| PPT-5 | Precipitation minus 5% |
| PPT-15 | Precipitation minus 15% |
| PPT-30 | Precipitation minus 30% |
| PPT+5 | Precipitation m 5% |
| PPT+15 | Precipitation plus 15% |
| PPT+30 | Precipitation plus 30% |
| RC | Rain cover |
| RP | Risk premium |
| SD-30 | Soil depth minus 30cm |
| SI | Sustainable intensification |
| SOC | Soil organic carbon |
| SPEI | Standardized Precipitation Evapotranspiration Index |
| SSA | Sub Saharan Africa |
| TAMSAT | Tropical Applications of Meteorology using SATellite and ground-based observations |
| VC | Vegetative drought cover |
| WII | Weather Index-based Insurance |

# 1. Introduction

## 1.1. Problem statement and background

Smallholder farmers in semi-arid West Africa are faced with several constraints consisting of economic, production and environmental aspects including poor soil fertility (Raimi et al., 2017), weak market infrastructure (Hansen et al., 2019) and lack of access to credit facilities (Mensah et al., 2017). At the same time, fluctuating market prices (Zhang et al., 2022), and high levels of intra- and interannual weather variability (Bogale, 2015) combine to make on-farm investments in intensification options very risky. The situation is anticipated to intensify as weather extremes become more frequent with climate change (IPCC, 2023). As poverty and food insecurity are prevalent in the region within farming communities (De Jager et al., 2018; Tsiboe et al., 2023), the intensification of on-farm production is widely promoted as a means to improve yield levels and average on-farm income (Danso et al., 2018; Pretty et al., 2011). With land expansion largely unsustainable due to biodiversity and associated ecosystem service loss (Putri et al., 2019), sustainable intensification (SI) of agricultural production is considered to be an effective alternative for smallholder farmers to increase their farm income (Gashu et al., 2019; Pretty et al., 2011). However, this is likely to become even more risky considering that weather-related risks including drought and floods leading to crop failures, are projected to increase under climate change (Hamsa & Bellundagi, 2017; Lesk et al., 2016; Trisos et al., 2022). Despite several initiatives aimed at promoting SI options in semi-arid West Africa (Gashu et al., 2019), there has been limited success due to the various constraints, widespread poverty and the riskiness of farming in the region (Tang & Hailu, 2020; Yin et al., 2016).

In the face of climate and market risks, smallholder farmers in SSA have adopted various coping strategies, including defaulting on loans, withdrawing children from school for farm work, and cutting back on household rations, among others (Birthal et al., 2012; Hansen et al., 2019). However, these measures do not offer lasting solutions and have development costs, as most of the affected households may not return their household consumption and farming activities to pre-shock levels (Boucher et al., 2024). Overcoming these challenges would require combining different risk management options that can support farmers in the short term while ensuring the development in the medium term of more sustainable and profitable farming systems. Several options have been proposed in the literature to reduce risk, such as the use of drought-resistant or stress-adapted crop varieties (Birthal et al., 2012), changing planting dates (Antón et al., 2013), conservation agriculture systems that include minimum tillage (Pannell et al., 2014), mulching (Alary et al., 2016) and crop rotations (Rusinamhodzi et al., 2011). However, risk reduction is insufficient under extreme climatic shocks and does not necessarily align with the investments needed for longer-term sustainability and livelihood improvement as farmers are likely to become insolvent in years with severe yield failures (Danso et al., 2018; Nafi et al., 2021). Here the need for a broad portfolio of risk management is needed, combining risk reduction with risk transfer (Di Marcantonio & Kayitakire, 2017; Sibiko et al., 2018), prudent risk-taking and savings among others (Holden & Shiferaw, 2004).

Informally, many farmers use livestock as a form of insurance. They are normally kept for providing the household protein requirements and on-farm traction, though they can be sold in years with extreme crop failure to provide liquidity (Herrero et al., 2013). However, this also comes at a cost, as farm animals require fodder obtained from crop residues, which may also serve an important purpose for improving soil fertility through incorporation into the soil (Alary et al., 2016; Nafi et al., 2021; Pannell et al., 2014). Formal insurance options that include crop insurance on the other hand have been discussed as alternative risk transfer measures (Ahdika et al., 2019; Leblois et al., 2014), which may enable farmers to invest in SI options in the face of climate risks (Aidoo et al., 2014; Bawa, 2019; Hansen et al., 2019; Laube et al., 2012; Traore et al., 2017). Several studies have highlighted the usefulness of these insurances particularly under extreme weather conditions, however, the adoption rate remains low, with reasons such as high premium prices, farmers' limited trust and understanding of contracts and faulty insurance designs given as the reasons for the low subscription rates (Arshad et al., 2016; Di Marcantonio & Kayitakire, 2017; Ntukamazina et al., 2017). While opinions concerning the benefits of various insurance types are divided (Afshar et al., 2021; Binswanger-Mkhize, 2012; Clarke et al., 2013; Ricome et al., 2017), in addition to their high transaction costs (Bulte et al., 2020; Rigo et al., 2022), many authors have expressed concerns that crop insurance is expensive for smallholder farmers and have highlighted the need for subsidies (Arshad et al., 2016; Binswanger-Mkhize, 2012; Carter et al., 2014; James et al., 2011; Shirsath et al., 2019). Index-based insurance has been proposed as an alternative and affordable option because their payouts are reliant on the realisation of an independent and transparent index rather than basing them on actual yield losses (Conradt et al., 2015), offering to reduce the high transaction costs (Rigo et al., 2022), minimise the adverse selection risk and promote an efficient and transparent pay-out process (Skees et al., 2001). However, these index-based insurance are also affected by basis risk and non-transparency of the index (Collier et al., 2009; Conradt et al., 2015; Tadesse et al., 2015), which affects the functionality and effectiveness of index-based insurance and leads to low product subscriptions.

Recognising the importance of insurance in stabilising farm income and as a safety net under extreme climatic or agronomic conditions, it is important to assess conditions under which insurance products do and do not provide benefits for certain groups of farmers, including the challenges associated with the design, supply, and demand of the products. Given the interactions among farming systems and a host of the soil-crop-water-animal-market complexity, system analysis tools are helpful to complement experimental and observational approaches to explore a range of options and conditions. System modelling tools that integrate biophysical and economic models can support a better understanding of trade-offs and synergies between various economic and environmental outcomes associated with farm management decisions considering for example, crop and livestock production, soil fertility-related processes, on-farm and off-farm labour availability, or crop response to weather and management (Barbier, 1998; Ewert et al., 2015; Feola et al., 2012; McDonald et al., 2019).

While there are several examples of modelling approaches that capture the effects of weather, price, and production risks on different farm household components, such as consumption and livelihood (Briner & Finger, 2012; McDonald et al., 2019; Zhang et al., 2022), to the best of our knowledge, none have included annual feedback on crop management as a result of modified farm-level decisions in response to weather influences on crop and fodder production. This is considered crucial in assessing the effects of extreme weather or input price spikes on crop management as a yield failure or lack of cash may result in farmers having to choose less expensive or more staple crops and management than intended before the shock. This may have important consequences when considering the implications for longer-term sustainability outcomes for environmental variables like soil organic carbon and biodiversity. Furthermore, the impacts of shocks and the assessment of risk management options can be analysed through scenario analysis (Arribas et al., 2017), models that are capable of simultaneously evaluating farmers' response to weather shocks and the subsequent effects on farm assets, including livestock or natural capital are still lacking. Previous studies have focused on optimising production under risks over a typical planning period, with few attempting to account for the effects of shocks on farm trajectories (van Wijk et al., 2014). Such models could help to specifically assess the effects of weather insurance on farm income under risks, providing more insights on such insurance contracts. While there is a growing literature on the challenges, opportunities and willingness to pay for insurance products in SSA (Bogale, 2015; Carter, 1984; Collier et al., 2009; Ntukamazina et al., 2017; Tadesse et al., 2015; Yakubu et al., 2016), few studies have examined the impact of weather index insurance contracts on farmers' income considering the large uncertainty in weather conditions. Such studies can support efforts to design weather index-based insurance products and highlight reasons for low subscriptions among smallholder farming households in SSA.

## 1.2. Research objectives and research design

Considering the described research gaps, fully described in Chapter 2, the main objective of this PhD thesis is to develop an integrated modelling approach to assess risk management options to improve livelihoods and longer-term sustainability outcomes in the face of high weather variability. This was investigated for the case of smallholder mixed farming systems in Northern Region, Ghana. The specific objectives of the thesis are:

1. To develop a generic bio-economic modelling framework that can capture and assess the probability of changes in farm resources in response to weather variability.
2. To evaluate the performance of different index-based insurance products regarding effects on smallholder farmers' income and assets.
3. To explore the effects of spatial, temporal and product basis risk on the effectiveness of weather Index-based Insurance (WII) to increase income and reduce asset loss.

## 1.3. Overview of the thesis structure

The thesis is structured as follows: Chapter 2 provides a review of relevant literature, whereas Section 2.1 highlights the risks facing smallholder farmers and different risk management options adopted by the farmers., Section 2.2 explores different modelling approaches, and Section 2.3 explores risk management options, including risk transfer and risk reduction options. The methods are presented in Chapter 3, illustrating the study area, the modelling framework, the data sources, the insurance product evaluated and the basis risk scenarios. The results of the thesis are presented in Chapter 4, while the discussions around the results of this thesis are presented in Chapter 5. Chapter 6 presents the general summary, the recommendations for future research and the contributions to knowledge.

# 2. Literature review

## 2.1. Insurance as a means of risk transfer

Several studies have proposed differing risk reduction options as effective means of risk management on the farms and as well enable farmers to make sustainable investments (Hansen et al., 2019). Some of the proposed strategies include the use of stress-adapted crop varieties (Birthal et al., 2012), changing planting dates (Traore et al., 2015), agroforestry systems, diversification or conservation agriculture. The latter include practices such as zero tillage (Pannell et al., 2014), mulching (Alary et al., 2016), and crop rotation (Rusinamhodzi et al., 2011) to minimise soil disturbance and maintain soil cover (Birthal et al., 2012; Pretty et al., 2011). However, some evidence shows that risk reduction as a stand-alone option may not improve yields on average or in bad years (Danso et al., 2018; Faye, Webber, Naab, et al., 2018), suggesting other risk management strategies, such as risk transfer (Di Marcantonio & Kayitakire, 2017; Sibiko et al., 2018), prudent risk-taking (Holden & Shiferaw, 2004) and savings (Farrin & Miranda, 2015), need to complement risk reduction.

Risk transfer strategies such as crop insurance have been extensively explored in the literature as an effective risk management approach (Ahdika et al., 2019; Leblois et al., 2014) . These studies position crop insurance not only as an efficient means to help farmers cope better with risks but also to enable risk-taking (Aidoo et al., 2014; Bawa, 2019; Hansen et al., 2019; Laube et al., 2012; Lichtenberg & Iglesias, 2022; Traore et al., 2017). This capacity to take on risks without fear of devastating losses and becoming trapped in chronic poverty is crucial for sustainable intensification (Barnett et al., 2008; Rigo et al., 2022). Other informal and temporary risk management strategies like liquidating assets, defaulting on loans, withdrawing children from school to work on farms as well as reducing household ration (Birthal et al., 2012; Hansen et al., 2019) are not able to insure the farming households against covariate shocks and they are associated with larger costs for the households in the long run (Rigo et al., 2022). However, despite the promise of these insurance products and efforts to promote them among smallholder farmers, adoption is remarkably low due to unprofitable terms among other reasons, leading various authors to suggest that subsidies are required for insurance products (Carter et al., 2014; James et al., 2011; Shirsath et al., 2019).

Different insurance products have been implemented across SSA including satellite-based, area-yield index insurance, and index-based livestock insurance among others (Ntukamazina et al., 2017). In Ghana, the Ghana Agricultural Insurance Pool (GAIP) was introduced in 2011, providing four insurance products including weather index insurance, area yield index insurance, multi-peril crop insurance, and an insurance product for poultry (Abugri et al., 2017; Afriyie-Kraft et al., 2020; Ankrah et al., 2021). However, like many other countries in SSA, farmers in the Northern Region of Ghana are faced with capital constraints, so very few farmers subscribed to the products (Afriyie-Kraft et al., 2020) due to lack of government subsidies (Ankrah et al., 2021). Generally, factors such as high premium rates, the economic behaviour of farmers, cognitive failure, and basis risks, among many others are reasons for the low acceptance of insurance in SSA (Arshad et al., 2016; Di Marcantonio & Kayitakire, 2017; Ntukamazina et al., 2017).

The low demand for these instruments calls for the need to evaluate risk transfer as part of larger risk management portfolios, combining different options and testing several scenarios. To date, there are few systematic studies or modelling approaches to assess the appropriate portfolio of risk management options as they vary across different farming contexts.

## 2.2. Risk and smallholder farming systems

Risks and uncertainties have been used interchangeably in the literature (Castro et al., 2018). Hübner et al. (2017) defined risk as an uncertain event whose outcomes affect the decision maker’s well-being. Distinguishing between risk and uncertainty Hamsa & Bellundagi (2017) defined risk as “imperfect knowledge where the probabilities of the possible outcomes are known and uncertainty exists when these probabilities are not known” (p. 448). Farmers in semi-arid West Africa are exposed to weather variability and market-related volatilities (Zhang et al., 2022), which together with illness and possible labour shortages combine to make their livelihood and farming operations very risky (Aidoo et al., 2014; Huet et al., 2020; Iddrisu et al., 2018). These risks put smallholder farmers in Northern Ghana in an extremely vulnerable position because the majority practice subsistence agriculture with low productivity (Iddrisu et al., 2018). These risks have many other economic and social implications for the farmers, as they are unable to meet their household needs and food requirements. This situation is worsened by the issue of climate weather-related risks, such as drought, flood and their related yield failure, which are projected to increase under climate change (Lesk et al., 2016; Trisos et al., 2022). Different coping strategies adopted by the farmers have not produced the desired outcome as in many cases they fall deep below the poverty lines (Birthal et al., 2012; Boucher et al., 2024; Hansen et al., 2019). This has led to many studies suggesting alternative risk management strategies such as the use of drought-resistant crop varieties, changing planting dates and conservation agriculture (Birthal et al., 2012; Pannell et al., 2014).

Climate-related risks have been discussed to create barriers to the adoption of improved technologies and practices (Farrin & Miranda, 2015; Hansen et al., 2019), whereby farmers are unable to make long-term investments or even take up innovations that could increase production because they cannot afford such investments. In addition, with these risks, the reluctance to adopt innovations increases due to the fear of failure as farmers are risk averse, they tend to avoid profitable but risky investments (Di Marcantonio & Kayitakire, 2017). Simulation models can be effective in assessing the effect of climate risk on farm management outcomes as heat and drought risks can be simulated through the crop model simulations, which are the main climatic risks faced by smallholder farmers in SSA. The simulations can also provide a probability distribution of crop yield data, which can capture risk due to yield variability.

## 2.3. Bio-economic farm models and frameworks for whole farm assessments

Ex-ante assessments of the possible outcomes of choices and policies are of particular interest to decision and policy makers. System modelling tools can provide valuable assessments by simulating various scenarios and predicting impacts (McDonald et al., 2019). System modelling approaches as described by Feola et al. (2012) include agent-based models, linear programming and system dynamics. Several models could also be combined to explain the complex interactions among socio-economic, bio-physical, and socio-ecological processes, which are often referred to as bio-economic farm models (Castro et al., 2018; Feola et al., 2012; Flichman & Allen, 2013; Wolf et al., 2015).

Bio-economic farm models (BEFMs) among others can be applied to assess the impacts of changes in technology and policies across a range of geographical and climatic conditions (Janssen & van Ittersum, 2007; Payraudeau & Van Der Werf, 2005). While many definitions of bio-economic models exist, Delmotte et al. (2013) defined BEFMs to consist of a biophysical component, which considers spatial and temporal variability of the performance (e.g. crop yield) as well as the impacts of agricultural activities. In simple terms, they combine aspects across disciplines e.g. agronomic and economics in mathematical programming models to provide multi-disciplinary and multi-scale solutions to farm resource allocation problems (Flichman & Allen, 2013; Janssen & van Ittersum, 2007; Louhichi, Flichman, et al., 2010).

Many authors have reviewed the use and application of BEFMs in literature (see Castro et al., 2018; Delmotte et al., 2013; Flichman & Allen, 2013; Janssen & van Ittersum, 2007; Payraudeau & Van Der Werf, 2005 for extensive details on BEFMs). There is a large diversity of BEFMs, including mechanistic and empirical models, positive and normative models, single and multiple objective function models, models incorporating risk and uncertainties and models incorporating time dynamics (i.e., static and dynamic models) (Janssen & van Ittersum, 2007). The inclusion of temporal dynamics is an important consideration in classifying BEFMs since the majority of BEFMs are static (Flichman & Allen, 2013; Janssen & van Ittersum, 2007; Robert et al., 2016). Comparing dynamic and static models, Castro et al. (2018) noted that dynamic models can be used to examine the effects of different mechanisms before, during and after their implementation. Static models are restrictive and conservative; they do not consider the changes in the objectives over time. They can show what happens over time but the element of time is not included in the models (Castro et al., 2018). Lehmann et al. (2013) developed a static bio-economic model for farmers in western Switzerland, which combined a crop growth model with an economic decision model that identified optimum management decisions. In their model, they maximised the farmers' utility while optimising farm scale management decisions under different climate and price scenarios. Janssen et al. (2010) and Louhichi et al. (2010) introduced a static, generic bio-economic farm model (The Farm System Simulator (FSSIM)), which is more suited for an advanced economy country context. FSSIM is linked to an econometric extrapolation model and a crop system model. Using mathematical programming, the model maximises the farmer's utility function subject to various resource and policy constraints. Ditzler et al. (2019) argue that in the smallholder farmer´s context, the farm enterprise is closely linked with their household dynamics and household consumption should be considered.

In 2013, Louhichi et al., adapted the FSSIM for a developing country context to develop FSSIM-Dev by adding household, perennial and aggregation modules of market conditions to the FSSIM. This overcame the challenge of assuming that production and consumption decisions for smallholder farmers in developing countries are separable. Both models assess the impacts of policies on the sustainability of agricultural systems. Groot et al. (2012) presented a bio-economic static whole-farm model (FarmDESIGN) which was expanded by Ditzler et al. in 2019. The model is a multi-objective optimisation model used to assess the interactions and trade-offs between socio-economic and environmental objectives, such as economic performances and organic matter balance. Castro et al. (2018) argue that multiple objective function models address land use problems in a more comprehensive way as compared to single objective function models of, for example, profit maximisation or risk minimisation. The model of Rădulescu et al. (2014) considered multiple objectives through the introduction of a mathematical programming model for crop planning that included weather, market and environmental risks. The objectives were to minimise the environmental risk, maximise the expected return and minimise the financial risk in the presence of a set of constraints. Semaan et al. (2007) developed a dynamic model to assess the effects of different policy measures on farmer's revenue and nitrate leaching. The model combined the Erosion-Productivity Impact Calculator (EPIC) crop growth model with a multiple objective mathematical programming model at the farm level. The economic decision model included a twofold objective of maximising the farmer's revenue and minimising the risk.

There has been an increase in the application of bio-economic models in Africa but there remain few models which have been applied at the smallholder level (Bidogeza et al., 2015). In 1998, Barbier combined a recursive and dynamic linear programming model with a biophysical model to predict yields and land degradation in Burkina Faso, concluding that population pressure affects intensification and investment in land conservation practices. Similarly, Holden & Shiferaw (2004) applied a bio-economic model to analyse the combined effects of land degradation, population growth, market imperfections and drought risk on household production, welfare and food security in Ethiopia. Louhichi et al. (2010) coupled a biophysical model to a non-linear dynamic model to estimate the amount of soil erosion generated in Tunisia. Bidogeza et al. (2015) developed a bio-economic model to analyse the impacts of soil erosion, family planning and land consolidation policies on food security in Rwanda.

However, most of these studies have focused on studying causal effects, including that of climate risk and price volatility, land degradation and soil erosion among others, with few investigating farmer´s responses to weather and production shocks. Economic models are well suited to describe farmers’ behaviour and decision-making process, but they do not account for the agroecological processes underlying agricultural production. Biophysical crop models are a significant part of the bio-economic model, in addition to providing the BEFMs with simulated grain and biomass yield, they can be used to assess climate change impact and risk (Ewert et al., 2015; Webber et al., 2022) and to show interactions with the level of intensification. They can also be applied to assess the relationships between land use, organic and inorganic fertilizer applications, and output in terms of production and change in soil quality (Feola et al., 2012; Kruseman, 2000). However, one major limitation of biophysical models is that farm management practices are considered as an exogenous input, which is quite constant even after a shock (Webber et al., 2014). To endogenize management decisions, a biophysical crop modelling framework could be linked with a farm simulation and optimisation model to form a bio-economic model. Linking these models in an integrated modelling approach will support the understanding of the complex and dynamic interactions and most importantly, the feedback among bio-physical, socio-economic, and institutional component levels in farming systems (Feola et al., 2012).

### 2.3.1. Consideration of risk in models

In the context of decision-making around intensification in West Africa, it is important to include risks in BEFMs as the decision to invest in fertilizers, improved seeds or a new practice can be very risky given uncertain weather and price conditions. Several key elements associated with farming including weather, market prices, and plant diseases among others are highly unpredictable (Arribas et al., 2017). There is, therefore, a need to consider risk elements on the farm level that affect farmers' decisions and investment options (Hardaker et al., 2004).

Risk can be included in models through stochastic and non-stochastic programming. Stochastic programming is an approach that involves optimising with uncertainty (probabilistic optimisation), while non-stochastic programming is deterministic in nature (robust optimisation) (Beyer & Sendhoff, 2007; Greenberg, 2005; Murty, 2003). Many stochastic programming models have been applied in literature, including quadratic risk programming (i.e. mean-variance analysis), minimisation of total absolute deviations (MOTAD), target MOTAD (the safety first model), chance-constrained programming and some methods with different variants of stochastic programming using discrete, dynamic or recursive approaches (see Arribas et al., 2017; Freund, 1969; Hazell et al., 1987; Kaiser & Messer, 2011).

A dynamic household model by Holden & Shiferaw (2004) combined a decision model with inter-temporal environmental feedback in turn influencing subsequent decisions. The study analysed the effects of droughts on household production, welfare and food security by incorporating risk due to stochastic rainfall. Louhichi et al. (2010) presented a bio-economic modelling framework, where they coupled the EPIC model to a non-linear dynamic programming farm model. With the model, they estimated soil erosion associated with current cropping systems. The model accounted for risk and uncertainty in two major parameters, i.e. yields and prices. Mosnier et al. (2009) developed a dynamic bio-economic model, which was used to simulate production decisions of suckler cow farmers (in France) in a risky environment. They focused on the management options of the farmers in the face of price and weather risks to avoid losses or to increase their income. Alary et al. (2016) developed a dynamic bio-economic model based on the optimisation of a utility function under multiple constraints to simulate the impact of technological innovations such as the introduction of direct seeding mulch-based cropping on household income. The stochastic optimisation of the expected utility function accounts for farmers' attitude to risk according to the target MOTAD approach.

Most of the models capture risk only in the objective functions while assuming that the constraints are deterministic. This is not entirely the reality as farm resources can also be a source of risk (Kaiser & Messer, 2011). Chance-constrained programming developed by Charnes & Cooper (1959) is best suited to capture right-hand side (RHS) risk in agriculture. Such RHS risks are caused due to fluctuations in weather, affecting the availability of farm resources for the farmers (Kaiser & Messer, 2011). Such models have been applied by Zhu et al. (1994) and more recently by Geng & Xie (2019).

## 2.4. Risk management

### 2.4.1. Weather index insurance

With the challenges surrounding crop insurance products, particularly that of moral hazards and adverse selection of multi-peril, in addition to the high transaction costs (Bulte et al., 2020; Rigo et al., 2022), WII has been proposed as an alternative in the literature, offering to reduce the high transaction costs (Rigo et al., 2022), minimise the adverse selection risk and promote an efficient and transparent pay-out process (Skees et al., 2001). Index-based insurance is proposed as an alternative option because the payouts are reliant on the realisation of an independent and transparent index rather than basing them on actual yield losses (Conradt et al., 2015). The indices are obtained directly by measuring the weather conditions at local weather stations (Conradt et al., 2015; Hill et al., 2019).

Several authors have suggested that WII can help to stabilise farmers' income in the face of climate risk (Adeyinka et al., 2016; Antón et al., 2013; Berg et al., 2009). For example, Ricome et al. (2017) used the ANDERS-CELSIUS model (ANDERS- Agricultural and Development Economics Model for the Groundnut Basin in Senegal and CELSIUS- Cereal and Legume crops Simulator under changing Sahelian Environment) to evaluate the potential of WII to improve farmers' income and its impact on adoption of more intensive cropping and livestock systems in Senegal, concluding that insurance can improve welfare of farmers in the driest area of Senegal.

However, despite the potential of WII to help smallholder farmers overcome the challenges that come with climate shocks, in SSA, the demand for these insurance products have not improved compared with the other insurance products (Clement et al., 2018), with many farmers opting for other alternatives in most pilot projects (Jensen et al., 2016). Several studies have highlighted reasons such as high premium rates, economic behaviours of farmers and non-transparency of the insurance contracts as some of the reasons for the persistent low subscription (Arshad et al., 2016; Di Marcantonio & Kayitakire, 2017; Ntukamazina et al., 2017).

### 2.4.2. Basis risks and its impact on weather index insurance

In addition to the challenges associated with WII, one main shortcoming of index insurance is the issue of basis risk borne by the farmers (Collier et al., 2009; Conradt et al., 2015; Jensen et al., 2016; Michael et al., 2015; Tadesse et al., 2015), which is a result of imperfect correlation between the index and the losses (Rigo et al., 2022). Basis risk can lower farmers' income when they suffer losses, and the indices are not triggered or increase their income when they do not suffer losses, but the indices are triggered. This, therefore, disincentivises the risk-averse farmers from purchasing these insurance contracts (Lichtenberg & Iglesias, 2022).

Typically, three types of basis risk exist, including spatial and temporal basis risk and basis risk due to design error also called product basis risk (Afriyie-Kraft et al., 2020; Dalhaus et al., 2018; Leblois et al., 2014; Liu et al., 2019). Spatial basis risk arises as a result of too far average distances between the weather stations to the farm (Afriyie-Kraft et al., 2020; Clement et al., 2018). Temporal basis risk arises when the insurance is not able to account for the losses due to differences in weather conditions during the sensitive growth stage of the crop (Clement et al., 2018; Dalhaus et al., 2018), i.e., the basis risk that arises as a result of neglecting the temporal patterns of rainfall in terms of intensity and frequency (Muneepeerakul et al., 2017), while product basis risk occurs due to a faulty index that is unable to predict the actual yield losses (Dalhaus et al., 2018). Given the considerable impact of basis risk on the effectiveness of WII, it is, therefore, important to understand the extent to which faulty indices can impact farmers' income under shock. Exploring this can improve our understanding of various forms of basis risk and their implications for WII. There have been several studies that have explored basis risk, coming up with various definitions (Hill et al., 2019; Liu et al., 2019), ways to manage it (Elabed et al., 2013) or reduce its effect (Dalhaus et al., 2018; Dalhaus & Finger, 2016) and the different types (Leblois et al., 2014), including extensive reviews of other studies (Clement et al., 2018).

Muneepeerakul et al. (2017) identified rainfall as an unreliable yield indicator, potentially increasing WII's basis risk. Kölle et al. (2021) conducted a comparative analysis of satellite-based indices versus meteorological indices, concluding that the former could be effective, contingent upon the data quality from satellites and yield records. Eltazarov et al. (2023) advanced index insurance quality by incorporating satellite-derived soil moisture data to mitigate basis risk in WII. Nevertheless, research evaluating the direct impact of basis risk on the incomes of smallholder farmers during shocks is scarce (Jensen et al., 2016). Furthermore, to date, no studies have concretely quantified the effect of basis risk on WII functionality.

# 3. Materials and Methods

## 3.1. Study area

The study was carried out for the Northern Region Ghana, located in the Guinea Savannah agroecological zone of Ghana, with a land area of about 26,000 km$^2$ (Northern Regional Coordinating Council, 2023). Until a recent re-demarcation into new administrative regions, the zone comprised three main regions, namely the Northern Region, Upper West Region, and Upper East Region. The Northern Region has a population of about 2.5 million inhabitants and the region is characterised by a period of extremely low rainfall between October / November and April / May, often referred to as the dry season, and a rainy season period usually from May to October (Braimoh & Vlek, 2004), with an annual rainfall between 750 mm and 1050 mm and an annual mean temperature between 22.4 $^0$C and 33.9 $^0$C. Impacts of climate change with frequent floods, droughts and bushfires are pronounced in the region (Abdul-Razak & Kruse, 2017; Alhassan et al., 2019; Iddrisu et al., 2018). Agriculture is the main occupation for the majority of the population as it employs about 70% of the population (Amikuzuno & Donkoh, 2012). Crops like maize, rice, soybeans, sorghum, cowpea, groundnut and tomato are the most commonly cultivated crops in the region, predominantly with intercropping (Callo-Concha et al., 2012), while livestock such as cattle, goats, poultry, and sheep are commonly kept by households in the region (Wossen et al., 2014).

## 3.2. Sampling technique and farm survey data collection

In 2020, a survey covering 700 households was conducted across the Upper West Region, Upper East Region, and Northern Region during the agricultural cropping season. The analysis was narrowed to 378 households from the Northern Region, specifically in the Tolon, Savelugu, and Mion districts, aligning with the thesis's regional focus. The datasets were used to develop a farm typology, based on socio-economic characteristics such as age, gender and farm resource endowments (mainly land and herd size). The data was clustered with principal components and cluster analysis into three farm types. These farm types were then used to sample farmers from the first survey for a follow-up in-depth survey before the 2022 planting season. 15 respondents were randomly selected from each of the farm types, resulting in a total of 45 households equally distributed among the farm types. From this data, detailed crop and livestock production data including household socio-economic data, on-farm and off-farm income, farm assets and farm production data were obtained, which were used to parameterise the model. Data were obtained through questionnaires added to the JotBi app developed within the CGIAR CASCAID project (CGIAR, 2020). Price data for year 2022 including crop and livestock prices were obtained at the current market price and validated by experts at the Savanna Agricultural Research Institute in Tamale.

### 3.3. Definition of the three farm types considered

The variables for the typology were selected based on literature, expert opinion, and local context (Berre et al., 2019; Gebrekidan et al., 2020; Shukla et al., 2019). Ten variables (Table 1) that best classify the households based on income and resource endowments in the dataset were used to cluster the farm households. First, the dataset was checked for missing data and outliers, and these were controlled for through imputation and list-wise deletion techniques as proposed by Kuivanen (2015) and Shukla et al. (2019). 340 households were retained from the 378 households due to missing data and extreme outliers. To construct the farm household typology, principal component analysis (PCA) and factor analysis on mixed data (FAMD) were carried out on the 340 households. The "FAMD" function within the "FactoMineR" package in R software (Version 4.0.2) was used (Le et al., 2008; R Core Team, 2023) because it is best suited for both continuous and categorical variables (Kassambara & Mundt, 2020); the package was also used to carry out hierarchical clustering to obtain the different typologies (Shukla et al., 2019). From the clustering, the farm households were classified into three farm types, comprising 61 low-resource-endowed farms (LRE), 181 medium-resource-endowed farms (MRE) and 98 high-resource-endowed farms (HRE) farms, respectively. After clustering the farm households, 15 farm households each were randomly selected from the farm types for a follow-up survey in 2022 and the integrated model was parameterised based on the follow-up survey and extensive expert discussions for a broad overview of the study area.

*Table 1. Summary of variables used for typologies*

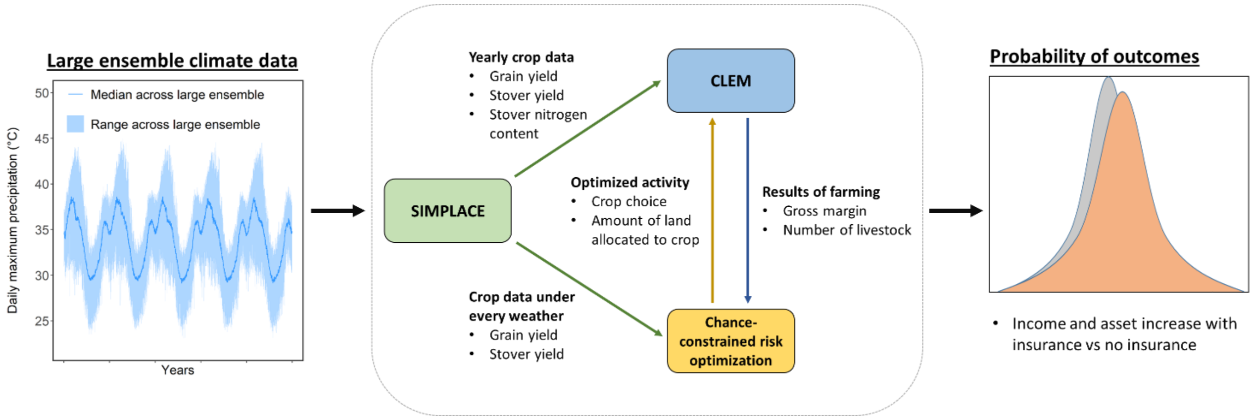
| Variable | Description | Unit |
|---|---|---|
| Age | Age of household head | Years |
| Cash at hand | Cash at hand at the beginning of the season | GHS |
| Sex | Sex of the household head | - |
| Household size | Number of individuals in the household | - |
| Herd size | Total herd size | - |
| Input costs | Total cost of production | GHS / year |
| Land size | Total land size | ha |
| Main crop | Main crop cultivated by farmer | - |
| Non-farm income | Annual household off-farm income | GHS / year |

| | | |
|---|---|---|
| Total annual income | Total annual household income | GHS / year |

GHS[1] is the Ghanian Cedi, which is the official Ghanaian currency

### 3.4. Modelling framework

An integrated bio-economic model was developed to simulate outcomes of annual resource allocation based on the optimisation of gross margins at the farm level while considering annual crop yield response to weather and management. The integrated model consists of a process-based crop model (SIMPLACE-website: https://www.simplace.net/) (Faye et al., 2018), a farm simulation model to account for resource flows during the year (The Crop Livestock Enterprise Model- CLEM) (Meier et al., 2019), and a newly developed optimisation model (see Figure 1) to plan future resource allocation. CLEM simulates financial and matter flows in response to annual grain and biomass yield from SIMPLACE, accounting for the effects of farm management options on resources. The final stocks from the CLEM simulation and the yield expectation from CLEM are input to the annual optimisation model. The three models were grouped to iteratively optimise the cropping pattern. A novelty in the integrated model is the use of a large ensemble climate forcing dataset, which allowed assessing probabilities of outcomes. A flow chart of the connected models, detailing the simulation steps, is provided in Figure 2 (Page 26). To explore the integrated model response under different degrees of weather variability, two weather scenarios were created from the ensemble data to represent good and bad weather conditions. The integrated model was further adapted and simulated to explore ex-post effects of a WII on farmer's income as well as to explore the effects of basis risk on the effectiveness of insurance by factorially combining WII contracts with replanting scenarios (details to be discussed later).



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[1] GHS as of August 23, 2023, exchanged for 11.24 GHS for 1 US Dollar

*Figure 1. A schematic depiction of the integrated model. The large ensemble climate data is used to simulate all scenarios, as shown on the left panel. The middle panel illustrates the integrated model comprising the Crop Livestock Enterprise Model (CLEM), the crop model (SIMPLACE), and an annual farm optimisation model. The probability of outcomes depicts the results of the model on the right panel, which are assessed in terms of probabilities.*

The key function of each model and data streams between the models are as follows:

1. SIMPLACE: simulates crop grain and biomass yield in response to weather, soil, and management. These simulations are passed to CLEM annually and to the optimisation model as yield distributions across all members within a weather scenario.
2. CLEM: simulates monetary and resource flows annually and outputs the balances of cash and herd size.
3. Optimisation model: optimises annual resource allocation and the production plan for CLEM.

### 3.4.1. Large ensemble weather data used to drive the crop model forcing data

To capture a large range of possible weather conditions that crops are exposed to, a large ensemble of climate modelling data was used. Large ensemble climate modelling data can produce several weather realisations for a given period and state of the climate, effectively sampling the whole distribution of possible weather (Deser et al., 2020; van der Wiel et al., 2019). A large ensemble of data, which contains 2000 instances (years) with characteristics consistent with the current climate was generated using the EC-Earth global climate model data (Hazeleger et al., 2012). EC-Earth is an Earth system model that represents atmosphere, ocean, land, and ice conditions. The large ensemble was used to capture as many extreme weather events as possible, consistent with the current climate which are often excluded with smaller datasets (including the historical weather record which is only one possible realisation of current climate among many). The ensemble consists of 400 members, with each member consisting of a 5-year simulation period representing the present-day global climate (as observed in 2011-2015). Details on the large ensemble experimental set-up can be found in (van der Wiel et al., 2019). The data were previously used in (Goulart et al., 2021; Van Der Wiel et al., 2020; Vogel et al., 2021; Zhang et al., 2022). The data were extracted for the grid point closest to the study site, Tamale ($09^0$ N and $00^0$ W). The modelled temperature and precipitation data were bias-corrected using station data from Nyankpala. For temperature, the daily maximum, minimum, and annual cycle were computed using a harmonic function (Liersch et al., 2018); simulated data were then corrected by the difference between the harmonic based on the observed data and the harmonic based on the simulated data as in Equation 1.

$$\mu(t) = a + \Sigma_{k=1}^{k} b_k \sin(kwt) + c_k cos\,(kwt) \tag{1}$$

where

$\mu$ = *Temperature (C)*

*t = Day of the year (1-366)*

*K = Order of harmonic function determined using Bayesian Information Criterion (BIC) (K = 4)*

*w = 2π/365.25*

*a, bk and ck are coefficients of the harmonic functions*

The precipitation was corrected monthly using a method from Vogel et al. (2021). The number of precipitation days of EC-Earth data was first corrected to the observed number to solve for the drizzle effects and the precipitation values of the days with precipitation amounts falling below a threshold were set to 0. The threshold was determined by matching the EC-Earth precipitation days to the observed precipitation days (≥0.1 mm $d^{-1}$). After correcting the drizzle bias, the EC-Earth monthly precipitation amount was corrected by a multiplicative factor to match the observed monthly precipitation amount.

### 3.4.2. Crop model simulations

A model solution in the SIMPLACE crop model framework was implemented to simulate crop growth in response to weather information and key management options (Ewert et al., 2015; Nafi et al., 2021; Webber et al., 2014). For the above-ground crop growth module in SIMPLACE, Lintul-5 (Wolf, 2012) was combined with a modified version of Slim Water for soil water dynamics (Addiscott & Whitmore, 1991). FAO-56 dual evapotranspiration method was used for evapotranspiration (Allen et al., 1998). To simulate the interaction between heat and drought, the heat stress module (Gabaldón-Leal et al., 2016), was combined with the canopy temperature module (Webber et al., 2016). The crop development, growth and grain and biomass yield were simulated in response to daily weather considering soil texture and depth, mineral nitrogen availability, and crop management practices such as sowing date, variety, and fertilizer applications. Water and nitrogen deficits both lead to reduced radiation use efficiency, which in turn reduces leaf area development expansion rates. Water deficit also resulted in higher canopy temperature affecting heat stress and increased assimilate partitioning to crop roots. Simulated yields were then reduced with an empirical reduction factor to account for yield and biomass reduction of imperfect weed, pest, and disease management by using the survey yield data and multiplicative factors. These were introduced to account for yield-reducing influences such as lack of seeds, labour, herbicides, pesticides etc. that SIMPLACE was unable to capture.

The SIMPLACE crop-modelling framework provides CLEM and the optimisation model with a simulation of biomass yield and crop nitrogen content as shown in Table 2. Crop model simulations were conducted for all the crops cultivated by the farmers namely: soybeans, groundnut, rice, and maize. These were obtained from the data obtained in the study area. Maize crop yields were simulated at three levels of nitrogen fertilizer application (i.e., maize with low, medium, and high fertilizer rates- fertilizer levels are given in section 3.4.3) because maize production in the study area is constrained by fertilizer application and intensity (Adzawla et al., 2021).

*Table 2. Variable inputs-outputs among models.*

| **Type of model** | **Base year (Year 1)** | | **Subsequent years (Year 2 – 5)** | |
|---|---|---|---|---|
| | **Variable input** | **Variable output** | **Variable input** | **Variable output** |
| Crop model | • Weather and soil condition<br>• Farm management | • Crop yield distribution<br>• Crop biomass | • Weather and soil condition<br>• Farm management | • Crop yield distribution<br>• Crop biomass |
| CLEM model | • Crop yield<br>• Crop biomass<br>• Initial production activities | • Net farm income<br>• Herd size | • Crop yield<br>• Crop biomass<br>• Farm production activities: crop choice | • Net farm income<br>• Herd size |
| Optimisation model | • Crop yield distribution<br>• Crop biomass<br>• Farm endowments | • Farm production activities: crop choice | • Farm endowments<br>• Resource shortages<br>• Cash at hand<br>• Herd size | • Farm production activities: crop choice |

### 3.4.3. Management of maize production and fertilizer assumptions

To classify maize production based on varying fertilizer application intensity, the following procedures were carried out:

1. The whole dataset was matched by crop production and the associated level of fertilizer used.
2. The farms cultivating maize with zero, low, medium, and high fertilizer levels were then grouped based on percentiles.
3. All land areas, crop types, and applied fertilizers declared as zero or blank were removed. This means that the land was either not cultivated or no fertilizer was applied.
4. Fertilizer rate per hectare was calculated for each plot with the formula in Equation 2:

$$qty_{fert} = \frac{Weight\ of\ a\ bag}{Declared\ area} \tag{2}$$

where

$qty_{fert} = Quantity\ of\ applied\ fertlizers\ in\ bag$

5. Nitrogen proportion was set to 15% unless the percentage is indicated, or the fertilizer product applied is urea.
6. Nitrogen rate per hectare was calculated with Equation 3:

$$N_{rate} = \frac{F_{rate} \times N_{prop}}{100} \tag{3}$$

where

$N_{rate} = Nitrogen\ rate\ in\ kg\ per\ hectare$

$F_{rate} = Fertlizer\ rate\ in\ kg\ per\ hectare$

$N_{prop} = Nitrogen\ proportion\ in\ percentage$

7. Grain yield from bags was calculated as (Equation 4):

$$Gn_y = \frac{Gn_a \times Grain_{weight}}{a} \tag{4}$$

where

$Gn_y = Grain\ yield\ from\ bag\ in\ kg\ per\ hectare$

$Gn_a = Grain\ amount\ harvested\ on\ land\ in\ bags$

$a = area$

$Grain_{weight} = Grain\ weight\ in\ kg$

8. Rows with zero grain yields per hectare were removed.
9. Maize was then categorized into three groups based on the nitrogen rate per hectare and the categories include maize with low fertilizer intensity: 0-30 N $ha^{-1}$, maize with medium fertilizer intensity 30-90 N $ha^{-1}$, maize with high fertilizer intensity greater than 90 N $ha^{-1}$.

From the classification, maize was simulated at three levels of nitrogen fertilizer application comprising maize with low fertilizer intensity applied with 17.5 kg N $ha^{-1}$ of fertilizer application, maize with medium and high fertilizer intensity applied with 49.4 kg N $ha^{-1}$ and 114 kg N $ha^{-1}$, respectively. In addition, groundnut, soybean, and rice are based on 4 kg N $ha^{-1}$, 17.4 kg N $ha^{-1}$, and 49 kg N $ha^{-1}$ applications, respectively.

### 3.4.4. Classifying climate ensemble into good and bad weather scenarios

Classifying climate ensemble members to either the good or bad weather scenario was done based on simulated grain yields for each ensemble member. Since the grain yield level varies among the crop types (e.g., rice yield above 3000 kg $ha^{-1}$ vs. soybean yield around 1000 kg $ha^{-1}$), the relative yield was calculated for each crop type (i.e., the yield of a given year divided by the average yield in all 2000 simulation years available in the dataset). Thereafter, the mean relative yield was calculated across crop types for each ensemble member (5-year simulation), and these mean yields were used to classify the ensemble members. The 30 highest and 30 lowest mean relative yield members were grouped into the good and bad weather scenarios (referred to as 30 ensemble weather in subsequent sections) and were included in the simulation to generate distinct weather responses for testing the integrated model.

### 3.4.5. The Crop Livestock Enterprise Model (CLEM)

The Crop Livestock Enterprise Model (CLEM), developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO), is an advanced farm management simulation tool. Leveraging biophysical data from crop-soil interactions, CLEM facilitates the exploration of farm management strategies by simulating the dynamics of on-farm resource flows against the backdrop of available resources. It comprehensively integrates various farm resources—labour, capital, land, and equipment—with key agricultural practices, including ploughing, weeding, and fertilizer application, to generate monthly assessments of critical indicators such as net income and food storage capacity (Meier et al., 2019). The model encompasses a wide range of inputs, from land and financial resources to labour (spanning both household and hired labour) and livestock feed stores, alongside an array of farm management activities that extend from crop to livestock management. These elements are meticulously tailored to each farm type within CLEM, offering annual projections of resource stocks and farm endowments throughout the simulation period. Notably, the model positions livestock as a strategic capital reserve, sold primarily under severe economic constraints to safeguard household consumption levels (Herrero et al., 2013). To parameterise CLEM, some assumptions were made including the assumption of off-farming income such as remittances, livestock sales as fixed income based on the data obtained from the survey and obtaining loans to supplement available capital based on the loan limit obtained from the survey data. Details of the underlying assumptions in the CLEM are documented in Appendix B.

### 3.4.6. Farm optimisation model

A whole farm chance-constrained model was developed, using the General Algebraic Modelling System (GAMS), version 31.2 with the solver DICOPT. The final parameterisation is based on the farmers' production activities in the region. Here, the sources of uncertainty constituting risk were the effects of weather scenarios on crop yields and the variation in herd size and cash at hand. To include these risks in the optimisation model, the chance-constrained risk optimisation model (Kim et al., 2013; Maher & Williams, 1999) was used as:

$$Max : CE = E(GM) - RP \tag{5}$$

where

CE = *Certainty equivalence of farmer's gross margin*

E (GM) = *Expected gross margin*

RP = *Farmer's risk premium*

subject to:

$$\Sigma_{j=1}^{J} a_{ij} x_j \ \leq b_i \ i = 1, \dots, n \tag{6}$$

where

$a_{ij} = Coefficient\ in\ ith\ constraint\ for\ variable\ x_j$

$x_j = Level\ of\ j_{th} activity$

$b_n(b_m) = Endowment\ of\ the\ nth\ input\ (mth$ "non certain" input)

$$Prob\ \left[\Sigma_{j=1}^{J}\ a_{mj} x_j \ \leq b_m\right] \ \geq \beta\ m = 1, \dots, M \tag{7}$$

$$E(GM) = \Sigma_{j=1}^{J} E(cm_j)x_j \tag{8}$$

where

$a_{nj}(a_{mj}) =$

$Technical\ coefficient\ matrix\ of\ nth\ input$ $(mth$ "non certain" input) $and\ the\ jth\ activity$

$\beta = Confidence\ level$

$E(cm_j) = Expected\ contribution\ margin\ of\ the\ jth\ activity$

$$RP = 0.5\rho\ \Sigma_{i=1}^{J}\Sigma_{j=1}^{J}V(cm_i, cm_j)x_ix_j \tag{9}$$

where

$\rho = Farmer's\ absolute\ risk\ aversion\ coefficient$

$V(cm_i, cm_j)$

$= Variance\ covariance\ matrix\ of\ the\ ith\ and\ the\ jth\ activity'scontribution\ margin$

$x_j \geq 0\ j = 1, \dots, m$

Equation 5 indicates that the risk caused by the fluctuation of the contribution margin of activities—which is caused by the variation in the yield—is included in the objective function of the model in the form of the farmer's risk premium. However, according to Equation 9, return fluctuations do not affect all farmers in the same way because they have different risk attitudes, which is reflected in their risk aversion coefficients. Another aspect of risk captured in this optimisation is related to the uncertainty in inputs such as cash at hand and herd size (see Equation (7)). It is assumed that the farmer is certain about the endowment of some inputs at the beginning of each year (Equation (6)) but is uncertain about others (Equation (7)). These constraints with uncertain outcomes are specified to be met with a given probability (confidence level) (Kim et al., 2013; Maher & Williams, 1999) i.e., a lower limit $(\beta)$ to ensure that the constraint will be satisfied (Kaiser & Messer, 2011). These constraints contain risks as their outcomes depend on several risky factors. To include these risks in the right-hand side of the optimisation model, the means and standard deviations were calculated from the distribution (i.e., cash at hand and herd size) and included in the chance-constrained programming. Following McCarl & Spreen, (1997), Equation (7) was entered into the optimisation model in the mathematical form of Equation (10):

$$\Sigma_{j=1}^{J} a_{mj}x_j \ \leq E(b_m) - \ \sigma_{b_m}(1 - \ \beta)^{-0.5} \tag{10}$$

where$E(b_m)$ and $\sigma_{b_m}$ are the expected value and standard deviation of $b_m$ (non-certain input), respectively.

Equation (9) includes a parameter for risk aversion to account for the risk behaviour of the farmers. As this parameter is subjective (Freund, 1956; Hardaker et al., 2004), the model was solved for different risk aversion coefficients ranging from low (0) to high (4) (McCarl & Spreen, 1997), each of the results was discussed with experts from the region, and the most suitable and efficient production plan was chosen for the farmers (Kaiser & Messer, 2011). Risk was incorporated into the objective function using a quadratic programming approach (Freund, 1956; Oxana et al., 2002; Preckel et al., 1987). The standard deviation for the total gross margin was calculated from the variance-covariance matrix of contribution margins for all production activities (Bidogeza et al., 2015). The household utility was measured using discretionary income, which is the income available for household use after paying for all essential expenses, including household consumption, clothing, school fees, etc. (Bidogeza et al., 2015; Labourte et al., 2009). The farming household comprises the household head, their spouses, children, or other people in the household who can earn any kind of income. Some assumptions made in the optimisation model include feeding the biomass from crop production (obtained from the crop model and updated yearly) to the farm ruminants, in addition to grassland and additional feed supplements that may be bought based on the feed requirements of the animals and availability. Further, as livestock are held as prized assets in the study area, livestock are parameterised as fixed assets and not sold, accounting for all associated costs to keep them. (see Appendix D for all assumptions for the constraints and mathematical equations included in the optimisation model).

## 3.5. The integrated model coupling

The three models (SIMPLACE, farm optimisation model and CLEM model) were recursively integrated on an annual basis for a period of 5 years. As a first step, the crop model simulations were conducted for all crop and fertilizer levels for all weather scenarios, scenario members, and years. The resulting data for the crop grain and biomass yields were stored in a database for access by the CLEM and optimisation models. Further, the resulting yield distributions were used as inputs for the optimisation model. Next, the CLEM and optimisation models were parameterised with initial farm management activities from the survey for each farm type. Starting with one weather scenario, the simulation proceeded by running the CLEM model for the first year of the weather ensembles, which resulted in a distribution of values for the herd size and cash at hand. The simulation starts by running CLEM for the first year using every ensemble member to obtain 30 independent outputs from the 30 ensemble members. Livestock were only considered sold if there was insufficient money to meet household expenditure, also considering available credit. The optimisation model then, simulates annual crop and land allocation, which are updated in CLEM the following year (i.e., year 2) as shown in Figure 2. This process was repeated for 5 years to obtain 30 different outputs from 30 ensemble members. This simulation is also repeated for different risk aversion parameters in the optimisation model. This is then repeated for each farm type and weather scenario.

The model results at the end of the 5-year simulation show the responses of the different farms to the various weather conditions and the integrated model was observed for how it captures shock, in this case due to weather variability. The same simulation was also done with CLEM without interacting with the optimisation model. This was done to compare the results of the current cropping pattern as simulated by CLEM (which is comparable to many studies in the literature) with the results of the integrated model (which provides a step forward in the possibility of making complete assessments).

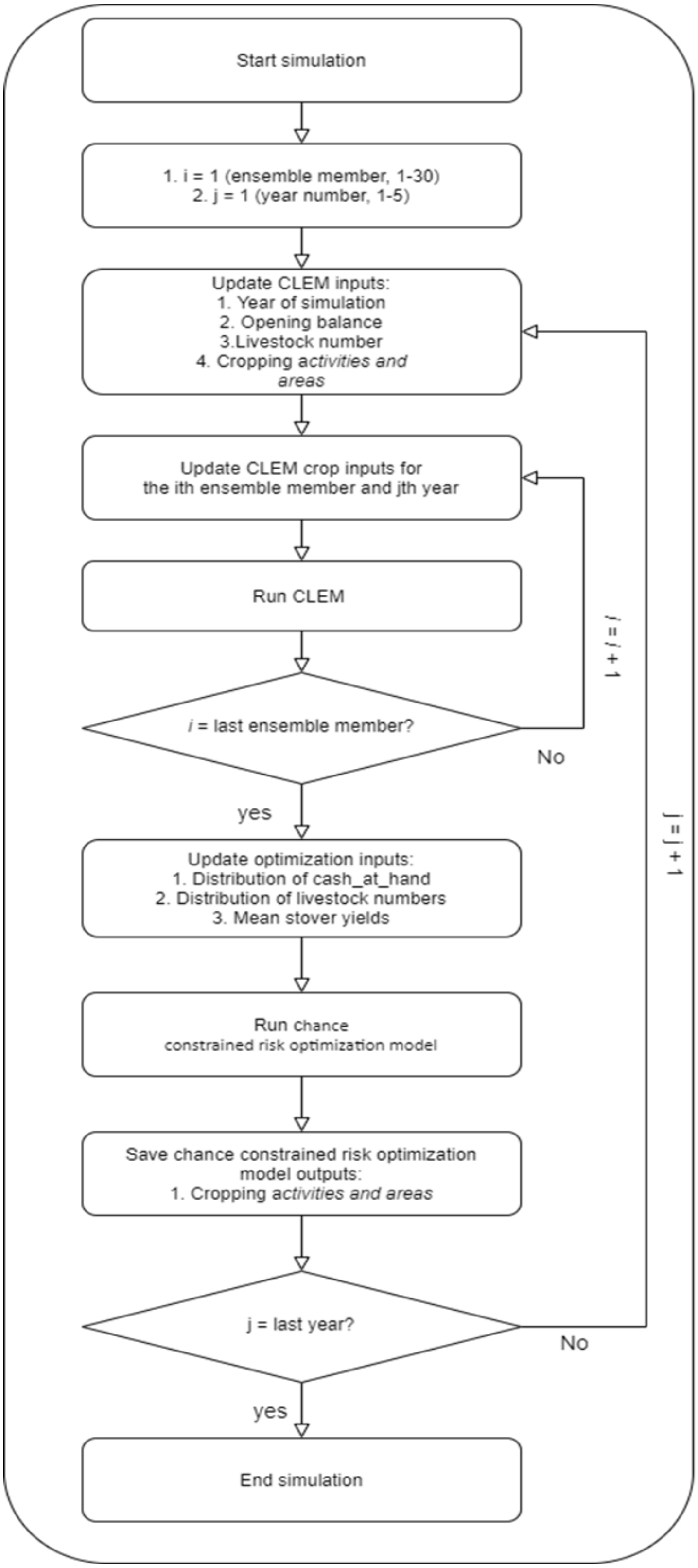

*Figure 2: Flow chart of the integrated model.*

## 3.6. Scenario definitions

### 3.6.1. Insurance-replanting scenarios

To explore the ex-post effects of a WII on farmers' income, the integrated model was adapted to include two different WII contracts: one less expensive product covering the germination phase and a more comprehensive product covering the whole growth period, both compared with a no-insurance reference. An agronomic management scenario of replanting (details later) in case of failure of crop establishment was also tested for each of the insurance cases. Simulations were conducted for the three insurance options: no insurance, seed insurance and full insurance in a factorial combination with the replanting scenarios as summarised in Table 3. These options were evaluated for each farm type.

*Table 3: Overview of insurance and replanting scenarios*

| **Insurance option** | **Growth stage** | **Replanting** | |
|---|---|---|---|
| No insurance | NA | No | Yes |
| Seed insurance | Germination | No | Yes |
| Full weather index-based insurance | Germination | No | Yes |
| | Vegetative | | |
| | Flowering | | |
| | Pre-harvest | | |

To incorporate the insurance contracts and the possibility of replanting in the event of yield failure, crop simulations were conducted with later planting dates, approx. 1 month after the initial planting date (APNI and CSIR, 2022) to assess yields that could be achieved if the farmers replanted. Further, indemnities were calculated for all possible weather scenarios and the premiums were also determined. However, for this, CLEM simulations were executed for all the 400-weather data ensemble (i.e., the good and bad weather classification was not used), generating 400 independent outputs. This was done to explore the response of farmers' income and assets under all weather conditions. In addition, insurance premiums and potential indemnity payments were incorporated into the farms' gross margins, thereby enhancing financial resilience. The updated model framework and set-up (flow diagram) are shown in Figures A1 and A2 in Appendix A1 and A2, respectively.

### 3.6.2. Basis risk scenarios

To explore the effects of basis risk on farmers' income, further simulations were conducted with crop yield obtained by varying daily precipitation to capture spatial basis risk, changing planting date to capture temporal basis risks, and changing soil depth as well as, field capacity to capture product basis risk. The simulations were conducted by factorially combining the different insurance options (no insurance, seed insurance and full insurance) with replanting scenarios under different yield outputs. For the spatial basis risk effect, daily precipitation was reduced by 15% down to 30% and increased up to 30%. Planting dates were also increased by 7 days up to 21 days and reduced to 14 days for temporal basis risk. Finally, the soil depth was reduced by 30cm and increased up to 30cm for product basis risk as shown in Table 4. For these scenarios, simulations were conducted only for the average farms in the study area as the objective was to capture the effects of basis risk on insurance but not the differences among the farms. The updated model framework is shown in Figure A3 in Appendix A3.

*Table 4: Overview of simulation experiment for basis risk scenarios*

| Basis risk | Insurance- WII | Daily precipitation changes | Changes in planting dates | Changes in soil (depth, field capacity) | Replanting |
|---|---|---|---|---|---|
| Spatial | No | NA | - | - | NA |
| | Seed | -30% | - | - | Yes |
| | | -15% | - | - | |
| | | -5% | - | - | |
| | | 0 | - | - | |
| | | +10% | - | - | |
| | | +30% | - | - | |
| | Full | -30% | - | - | |
| | | -15% | - | - | |
| | | -5% | - | - | |
| | | 0 | - | - | |
| | | +10% | - | - | |
| | | +30% | - | - | |
| Temporal | No | - | NA | - | NA |
| | Seed | - | -14 days | - | Yes |
| | | - | 0 | - | |
| | | - | + 7days | - | |
| | | - | + 21 days | - | |
| | Full | - | -14 days | - | |
| | | - | 0 | - | |
| | | - | + 7days | - | |
| | | - | + 21 days | - | |
| Product | No | - | - | - | NA |
| | Seed | - | - | -30cm | Yes |
| | | - | - | 0 | |
| | | - | - | +30cm | |
| | Full | - | - | -30cm | |
| | | - | - | 0 | |
| | | - | - | +30cm | |

### 3.7. Weather index insurance options

Northern Ghana is characterized by high weather fluctuations, with increasingly pronounced impacts of climate change (Abdul-Razak & Kruse, 2017; Alhassan et al., 2019). The largely subsistence farming households regard maize as the most important staple crop (Antwi-Agyei et al., 2018), comprising a large share of their land allocation (Ankrah et al., 2021; Danso et al., 2018; Lucas et al., 2019) and household consumption (Nti, 2008). Therefore, in 2023, WII products were developed for maize in collaboration with ACRE Africa. ACRE Africa is an insurance service provider in sub-Saharan Africa that provides end-to-end risk mitigating options for farmers including access to credit and input, and insured risk (https://acreafrica.com/). The choice to develop and assess insurance solutions only for maize was based on several considerations. First and foremost, maize response to nitrogen fertilizer in the region is highly variable, particularly with rainfall amount and water availability (Danso et al., 2018), making the investment in fertilizer very risky and potentially a case where economic returns of fertilizer use could justify the use of insurance. Other reasons included the interest of ACRE-Africa in the analysis of income effects of such a product and our desire to limit the complexity of the study to one crop. Additionally, soybean is commonly grown in the region under contracts, which preclude the use of an insurance product, though likely with less favourable terms. The product designed here addresses excess and deficit rainfall although temperature also has an impact on the crops, including driving drought stress. Precipitation alone was considered as fluctuations in rainfall are considered as the major risk that is faced by farmers in sub-Saharan Africa including Ghana (Haile, 2005) and not heat stress (Faye et al., 2018). Temperature, which is not as variable, has been indirectly considered in the setting of the precipitation index trigger. In other areas where temperature is a major risk, these contracts can be adapted to consider the two elements of risk.

These contracts were developed to achieve the second objective of this thesis of evaluating performance of index-insurance products. To include the insurance options in the optimisation model, Equations 8 and 9 in the optimisation model were updated as Equations 11 and 12 respectively:

$$E(GM) = \sum_{j=1}^{J} E\left(cm_j + ind_j\right)x_j \; - RP + R - PR \tag{11}$$

where

$ind_j is\ the\ indemnity\ recieved\ for\ the\ jth\ activity\ and\ PR\ is\ the\ premium.$

$R =$ *all income from non-agricultural sources i.e., off-farm income, income from remittances etc.*

$PR$ is the insurance premium

$$RP = 0.5\rho \sum_{i=1}^{j} \Sigma_{i=1}^{j} \ v(cm_i + ind_j, cm_j + ind_j)x_i x_j \qquad (12)$$

where

$RP$ is the risk premium

*$\rho$ is the farmer's absolute risk aversion coefficient*

$v(cm_i + ind_j, cm_j + ind_j)$ *is the variance-covariance matrix of the ith and the jth activity's contribution margin and the indemnities*

As in Equation 12, the contribution margin and indemnities of maize were simulated in different scenarios. The gross margins include income from crop production, off-farm income due to employment, income from remittances, and income from poultry sales as obtained as from the survey. Non-agricultural income sources here are fixed, i.e., they are not subject to risk (Lien et al., 2023), therefore they are not included in the calculations of risk premium in Equation 12 above.

The insurance product developed here covers a period of 120 days with a specific planting date and comprises four stages, namely germination drought cover (GC), vegetative drought cover (VC), flowering drought cover (FC) and pre-harvest or excessive rain cover (RC) based on the growth phase of the crop (Skees et al., 2001). To choose an optimal planting date, the planting dates from the survey were observed (average planting date from the survey: June 12th). Further, the dates were discussed with experts who are familiar with the region and the current operations of the farmers, and they confirmed that 10th June is the optimal planting date stressing that most farmers plant on this date. This is also confirmed in the study carried out by Freduah et al. (2019), which states that June is usually regarded as the normal planting date in Northern Ghana, while May and July are respectively early and late planting dates in the region. Furthermore, the affordability and efficiency of two insurance products, namely seed insurance, and the full WII cover were compared. The latter comprises all the covers from day one to day 120. Seed insurance is an index insurance that covers the seed germination stage of the maize crop. The cover starts from day 1 of planting to day 21 after planting. The premium is attached to the purchase of hybrid maize seeds, and the price paid per kg will include the sum of the price of seeds and the premium for the insurance. The full WII product covers the entire growth cycle, including GC (duration given above), VC from 21 to 65 days after planting, FC from 65 to 95 days after planting while the RC covers from 90 to 120 days after planting. The combination of these four stages of insurance cover makes the full weather index insurance cover.

### 3.7.1. The weather indices

Both index products utilize daily rainfall observations from the Tamale (09$^0$ N and 00$^0$ W) grid point to assess risk during the cropping season. Here the extracted data from EC- Earth global climate model data for years 2011 to 2015 was used to calculate the weather index. This data was used because they are the same data used to run the integrated model, and this would ensure consistency. This was compared with the TAMSAT dataset for the same years, which gave comparable results. Triggers are set based on rainfall deficits and excesses per growth phase of the historical rainfall events. For the index, temperature and evapotranspiration were not considered because the aim was to develop insurance contracts that are as close to the study area as possible. Rainfall deficits and excesses were only considered because fluctuations in rainfall are considered the major risk faced by the farmers in the region (Haile, 2005). In addition, the standardized Precipitation Evapotranspiration Index (SPEI) requires additional inputs to compute potential evapotranspiration, which may increase the uncertainty (Hoffmann et al., 2020), especially in areas where good-quality and high-resolution climate data are missing, such as the study site of this thesis. Meanwhile, the precipitation-based index is more straightforward to calculate and thus easier to communicate with farmers. In addition, the drought stress in such regions is largely influenced by soil characteristics. The soil is significantly degraded, and thus, water holding capacity is extremely low. This implies that the meteorological drought index should be linked with soil data to represent drought stress better.

The trigger for the growth phase where drought is being monitored was determined by calculating the 5$^{th}$ percentile of the average daily observed rainfall data as represented by Equation 13 and during the maturity phase where excessive rainfall is the main peril, the trigger was determined by 95$^{th}$ percentile of the average daily observed rainfall data, as shown in Equation 14.

$$\mathrm{T_{phase}} = \mathrm{P0.05}(\mathrm{\mu}(\Sigma^{d}_{phase})) \qquad (13)$$

where

$\mathrm{T_{phase}} = Trigger\ for\ GC, VC\ and\ FC\ growth\ phase$

$\mathrm{P0.05} = \mathrm{5th\ percentile}$

$$T_{phase} = P0.95(\mu(\Sigma^{d}_{phase})) \qquad (14)$$

where

$\mathrm{T_{phase}} = Trigger\ for\ RC\ growth\ phase$

$\mathrm{P0.95} = 95\mathrm{th\ percentile}$

### 3.7.2. Indemnities

Indemnities were computed individually for each growth phase. For the GC phase, the cumulative rainfall over 14-day intervals was calculated starting from day 1 after planting until day 21 after planting (i.e., from day 1 to day 14, till day 8 to day 21). For the VC phase, the cumulative rainfall received every 21 days after planting, i.e., day 21 to 41 up to day 45 to 65 was calculated. During any period of 21 days, if the total rainfall received is less than or equal to the trigger values for the VC phase, a loss will be considered to have occurred. The same calculations were made for the FC and the RC phase observing daily cumulative rainfall every 14 days and every 21 days, respectively. For the full insurance cover, the maximum payable loss cannot exceed 100% of the input costs, the payable loss is divided into 4 for all growth phases, comprising 25% each as shown in Table 3. The number of intervals for each growth phase based on the daily rainfall data was estimated in Equation 15 to determine the loss compensation per phase.

$$N_{interval} = (N_{Dphase} - R_{cumP}) + 1 \tag{15}$$

where

$N_{interval} = Number\ of\ intervals\ per\ phase$

$N_{Dphase} = Number\ of\ days\ per\ phase$

$R_{cumP} = Cumulative\ rainfall\ days\ for\ each\ phase$

The loss compensation per interval was determined by dividing the maximum loss payable in each phase by the total number of intervals as shown in Table 5. The number of intervals where the trigger is set for each phase was then obtained. The number of intervals with the trigger set was then multiplied by the loss compensation per interval to obtain the percentage of input costs to be paid per phase.

*Table 5: Input data for indemnities*

| Insurance type | Phase | Maximum loss payable* | Number of days in phase*** | Cumulative rainfall days** | Number of intervals | Loss compensation per interval | Cost included per phase |
|---|---|---|---|---|---|---|---|
| Seed insurance cover | Germination | 100% | 21 | 14 | 8 | 12.5% | Seed costs<br>Sowing costs |
| Full insurance cover | Germination | 25% | 21 | 14 | 8 | 3.1% | Seed costs<br>Sowing costs |
|  | Vegetative | 25% | 45 | 21 | 25 | 1% | Fertilizer costs<br>Herbicide costs |
|  | Flowering | 25% | 30 | 14 | 17 | 1.5% | Weeding costs |
|  | Pre-harvest | 25% | 30 | 21 | 10 | 2.5% | Harvest costs |

* *Maximum loss is equal to total input costs covered per phase*
***days per interval used to calculate the cumulative rainfall that is compared to the trigger value*
**** these days can overlap*

The loss compensation per interval shown in Table 5 above was used to calculate the percentage of input costs to be paid if there is a payout to the farmer. In addition, the input costs to be paid depends on the growth phase of the crop (Table 5). For the seed insurance, there are no partial payments of indemnities, i.e., if the index is triggered the farmers get paid but if not, the farmer does not get paid. This is because the claims payouts are meant to facilitate the farmers to replant. To obtain a single payout for the seed insurance, all the indemnities in the germination phase that were greater than 0 were averaged i.e., cases where there were payouts.

### 3.7.3. Insurance premium

The insurance premiums for the different insurance contracts used for the study were calculated by using the burning cost analysis method, which is an estimation of the expected losses for an insurance cover based on historical claims (Parodi, 2014). Historical payoff average data (HPAD) from 1983 to 2022 for Latitude 9.375 and Longitude -1.125 were obtained from ACRE Africa and this data was averaged to obtain the historical payoff average (average losses). The HPAD are location specific, and they indicate the percentage of historical claims at different growth phases of the crops. The weather data used for the historical payoffs were obtained from TAMSAT (website: https://gws-access.jasmin.ac.uk/public/tamsat/) for the Northern part of Ghana region. The region was divided into the TAMSAT grid points of 4 km by 4 km resolution. This historical data ensures that the premiums are farm-specific, reducing adverse selection problems (Bucheli et al., 2021). Further, the capital loadings were estimated; an extra cost added to the insurance policy to cover for unanticipated losses (Sinha, 2013), which is also one of the key components of the risk premium. This is included because if the actual losses are significantly greater than the average, the insurance company would require funding from other sources to cover the claims (Parodi, 2014). It was calculated by subtracting the calculated average losses from the average catastrophic losses that are based on those losses exceeding a certain threshold (95th percentile) and multiplying it by the average cost of borrowing for the insurer as shown in Equation 16.

$$CL = A_{cb} \times (P0.95 - A_l) \tag{16}$$

where

$CL = Capital\ loading$

$A_{cb} = Average\ cost\ of\ borrowing$

$P0.95 = 95th\ percentile$

$A_l = Average\ losses$

The average cost of borrowing as obtained from ACRE Africa was 10% and an additional 20% of input cost was added as loading for expenses, commission, taxes on agriculture insurance contract and profit of the insurer. The pure premium was calculated as the sum of average losses and the capital loadings (Benjamin, 1986) in Equation 17. The gross premium was then calculated by adding the pure premium, the commissions and expenses as shown in Equation 18.

$$\mathrm{Pr} = CL + \text{Average losses} \tag{17}$$

where

*Pr = Pure premium (pure risk)*

$$\mathrm{GP} = Pr + \Sigma(C_m) \tag{18}$$

where

*GP = Gross premium*

$C_m$ = $Commissions$

With the additional 20% added for commission, this implies an assumption of 20% loading on the pure premium. This should cater for the taxes, expenses, and commissions. The 20% is just an assumption benchmarking based on the previous markets in SSA that ACRE Africa has worked in, and this is always subject to change based on the commercial arrangements.

### 3.8. Replanting and no-replanting

Replanting after crop failure due to low or excessive rainfall is an effective measure of offsetting yield losses (Sisterson & Stenger, 2013), although farmers may choose not to replant due to liquidity concerns (Amare et al., 2018). To explore the effects of this additional risk management measure, options for replanting during an extreme case of crop failure were included. The crop model simulated yields for an alternative planting date (i.e., July 10- one month after the first planting), with the same management practices as highlighted above. These simulated yields were used to replace extremely low yields (due to failures of crop establishment) in the first planting. For the farmers to replant (in both the seed and full insurance options) after an extreme case that leads to crop failure, the indemnity payment indicating the losses must exceed a 75th percentile threshold (i.e., the highest 25%) of the indemnity payments. Replanting costs were also added for replanting scenarios, and these included the costs of seeds and sowing associated costs. In the case of total yield loss and for the no-replanting scenarios, it was assumed that the corresponding yields for these extreme cases were zero. This was done to avoid the disparities and inaccuracies of accounting for yield losses during crop yield failure.

# 4. Results

## 4.1. Farm Typology

The sampling method applied resulted in the following farm typology, labelled as low-resource-endowed farms (LRE), medium-resource-endowed farms (MRE), and high-resource-endowed farms (HRE). The LRE farms as shown in Table 6 are farms with relatively smaller land and household sizes. The MRE farms are composed of predominantly small household sizes, with relatively average land size, while the HRE farms are farms with large household sizes and relatively large farm sizes.

*Table 6: Average socioeconomic information of different farm types*

| | Unit | LRE* | MRE* | HRE* |
|---|---|---|---|---|
| Adult in household | | 1 | 2 | 2 |
| Children (between 6 and 18) | | 1 | 1 | 5 |
| Children (less than 6) | | 0 | 0 | 2 |
| Remittances | GHS/year | 300 | 338 | 843 |
| Non-farm income | GHS/year | 567 | 1431 | 482 |
| Income from livestock sales | GHS/year | 500 | 441 | 1014 |
| Farm maintenance cost | GHS/year | 150 | 208 | 311 |
| Energy spending cost | GHS/year | 100 | 83 | 170 |
| Household living cost | GHS/year | 120 | 735 | 981 |
| Cash at hand (beginning of the season) | GHS/year | 126 | 1331 | 2393 |
| Average amount of loan | GHS/year | 47 | 1906 | 2536 |
| Loan rate | % per month | 8 | 8 | 8 |
| Input expenses (GHS) | GHS/year | 73 | 663 | 1757 |
| Total land area (hectare) | ha | 0.9 | 4.0 | 6.9 |
| Machinery rental cost (GHS) | GHS/year | 148 | 275 | 462 |
| Cattle | | 12 | 6 | 6 |
| Goat | | 2 | 9 | 8 |
| Sheep | | 0 | 3 | 6 |
| Poultry | | 14 | 19 | 18 |
| Animal supplement costs (GHS) | GHS/year | 12 | 61 | 105 |
| Veterinary visit cost | GHS/year | 0 | 10 | 25 |

**LRE represent low-resource-endowed, MRE represents medium-resource-endowed and HRE represents high-resource-endowed farms, respectively.*

The household size has an impact on farm production, as in many cases they serve as labour for farming activities (Nyuor et al., 2016). On the one hand, this can imply a relatively cheaper source of labour for the HRE farms compared with the LRE and MRE farms. On the other hand, a large household size means that more people in the household have food requirements. The positive correlation between household size and farm size found in this study agrees with the real farms in the study area, as highlighted by Ngeleza et al. (2011)

## *4.2.* Economic analysis *of the current situation*

The modelled farm income comprises both on-farm and off-farm income, which includes income from selling farm products and off-farm labour among other income sources. Maize is mainly cultivated as a food crop in the region, with relatively low gross margins (Table 7) per hectare, especially when household labour costs are accounted for. Rice, on the other hand, is the most profitable crop in the region, which is highlighted by a relatively high gross margin compared with the other crops (Table 7). Although maize crop has the same price (1.7 GHS $ha^{-1}$) regardless of the fertilizer intensity, maize with high fertilizer intensity has about five times more average yield $ha^{-1}$ compared to maize with low fertilizer intensity. Considering also that the difference between the variable cost of production between these fertilizer levels is only about five times more in maize with high fertilizer intensity, this makes high fertilizer intensity maize preferred to low fertilizer intensity maize for household consumption. Table 7 was calculated based on the current production activities of the farms in the study area.

*Table 7: Average contribution margin per crop per farm (in GHS ha$^{-1}$) based on current production data.*

| **Cost-benefit table with survey data** | | **Maize-low** | **Maize-medium** | **Maize-high** | **Soybean** | **Upland rice** | **Groundnut** |
|---|---|---|---|---|---|---|---|
| | Tillage | 1.5 | 3.4 | 5.1 | 2.1 | 3.6 | 4.1 |
| Labour requirements (Man-days per ha) | Fertilization | 6.0 | 20.1 | 20.7 | 5.1 | 4.9 | 0.2 |
| | Sowing | 13.4 | 36.1 | 43.7 | 20.9 | 7.9 | 35.1 |
| | Weeding | 13.7 | 39.2 | 56.6 | 25.0 | 52.3 | 39.3 |
| | Harvesting | 16.4 | 50.5 | 58.9 | 40.5 | 55.9 | 54.6 |
| | Threshing | 4.3 | 5.9 | 21.2 | 8.4 | 5.7 | 12.3 |
| | **Total** | **55.3** | **155.2** | **206.2** | **102.0** | **130.4** | **145.6** |
| Input cost (cedi per ha) | Tillage | 88.3 | 146.7 | 254.8 | 151.5 | 377.4 | 267.5 |
| | Fertilizer + service | 210.4 | 1234.6 | 2165.6 | 209.6 | 680.1 | 34.5 |
| | Seed + service | 19.4 | 15.5 | 57.2 | 128.5 | 111.6 | 113.1 |
| | Herbicide + service | 77.2 | 121.1 | 398.5 | 110.4 | 185.8 | 157.8 |
| | Harvesting | 13.8 | 27.3 | 70.4 | 28.2 | 26.8 | 40.5 |
| | Threshing | 15.2 | 6.5 | 55.4 | 27.2 | 20.8 | 44.1 |
| | **Total** | **424.3** | **1551.7** | **3001.9** | **655.3** | **1402.4** | **657.5** |
| Total variable cost (cedi per ha) | | 1530.5 | 4654.7 | 7126.5 | 2696.3 | 4011.2 | 3570.4 |
| Average yield (kg per ha) | | 660.6 | 2162.2 | 3294.7 | 1600.9 | 4229.0 | 3037.3 |
| Crop price (cedi per kg) | | 1.7 | 1.7 | 1.7 | 1.8 | 1.5 | 1.7 |
| Total revenue (cedi per ha) | | 1101.0 | 3603.6 | 5491.2 | 2935.0 | 6343.5 | 5062.2 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Gross contribution (cedi per ha) | 676.7 | 2051.9 | 2489.3 | 2279.6 | 4941.1 | 4404.7 |
| Gross margin (cedi per ha) | -429.5 | -1051.1 | -1635.3 | 238.7 | 2332.4 | 1491.9 |
| Labour cost/kg | 0.08 | 0.07 | 0.06 | 0.06 | 0.03 | 0.05 |
| Production cost/kg | 2.32 | 2.15 | 2.16 | 1.68 | 0.95 | 1.18 |

Data for the table were obtained from the survey, and they are used to parameterise the model.

## 4.3. Optimal allocation under various weather conditions

### 4.3.1. Crop yield

Figure 3 shows the distribution of crop yield in the bad and good weather scenarios as simulated by SIMPLACE. As expected, the yield from maize with a low fertilizer rate was the lowest among all maize fertilizer rate crops, and the yield was not so different under the two weather scenarios because it is limited more by nutrient deficiency than by rainfall. Rice is a high-yielding crop in the area as it produces about 4000 kg ha$^{-1}$ on average in good weather. For maize crops, variability in the yields was generally higher in the bad years compared with the good years and increased with the amount of fertilizer applied.

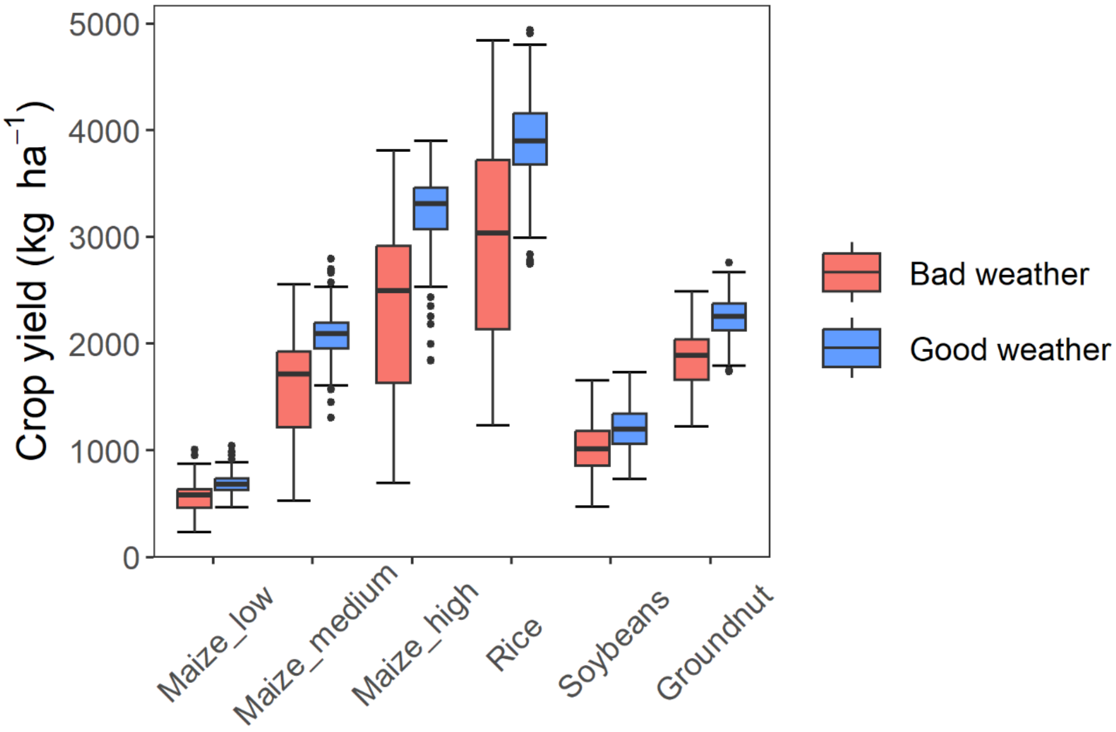

*Figure 3. Distribution of crop yields for the two weather scenarios (good and bad). Red bars show the distribution in "bad" weather ensemble members, and blue bars show the distribution in "good" weather ensemble members. The boxplots indicate the 25th to 75th percentile. The black dots represent outliers. The figure is obtained based on the yield from the 30 ensemble members.*

### 4.3.2. Optimal land allocation

The optimal cropping pattern for each farm type under both weather scenarios is presented in Figure 4. These cropping patterns were obtained by annual optimisation of the gross margins with a risk aversion coefficient of 0.001, considering yield variability. Annually, simulations from CLEM produce cash and livestock balances, which are included in the optimisation model for annual optimisation. For the current cropping simulation, both the LRE and MRE farms cultivated a high share of maize with low fertilizer intensity (28% and 33% of their land area, respectively), which is expected due to the high cost of fertilizers in the study area (Daadi & Latacz-Lohmann, 2021). The HRE farms, on the other hand, were able to invest in fertilizers to cultivate a high share of maize with medium fertilizer intensity because they could afford it. However, under the bad weather scenario, all farm types allocated their land to maize with low fertilizer intensity only, and the proportion of land allocation to maize declined considerably to 5% and 1% for LRE farms and MRE farms, respectively. This occurred because farmers lacked the liquidity to purchase fertilizers due to low productivity. Although many studies have highlighted that maize yield can be increased through increasing fertilizer application rates (Markovi et al., 2021; Mueller et al., 2012), Leitner et al. (2020) noted that water availability is another major limiting factor of maize yield. In addition, the total land area cultivated by MRE and HRE farms became much smaller, reducing from 4 ha and 5 ha to 1 ha and 2 ha, respectively, due to the poor yield under bad weather scenarios. Farmers were better off allocating a large share of their land to groundnut and soybeans under the bad weather scenario as this can increase liquidity through sales. As the weather scenario changed from bad to good, the land share for cash crops increased for all the farm types. In addition, under the good weather scenario, the need to diversify the crop choice reduced, and this was evident with the cropping patterns for all the farm types, where over 90% of the land area was allocated to rice for LRE farms and more than 80% was allocated to rice and groundnut for MRE farms (see Table S2 in Appendix E for the results of the cropping activity under changing risk aversion coefficient).

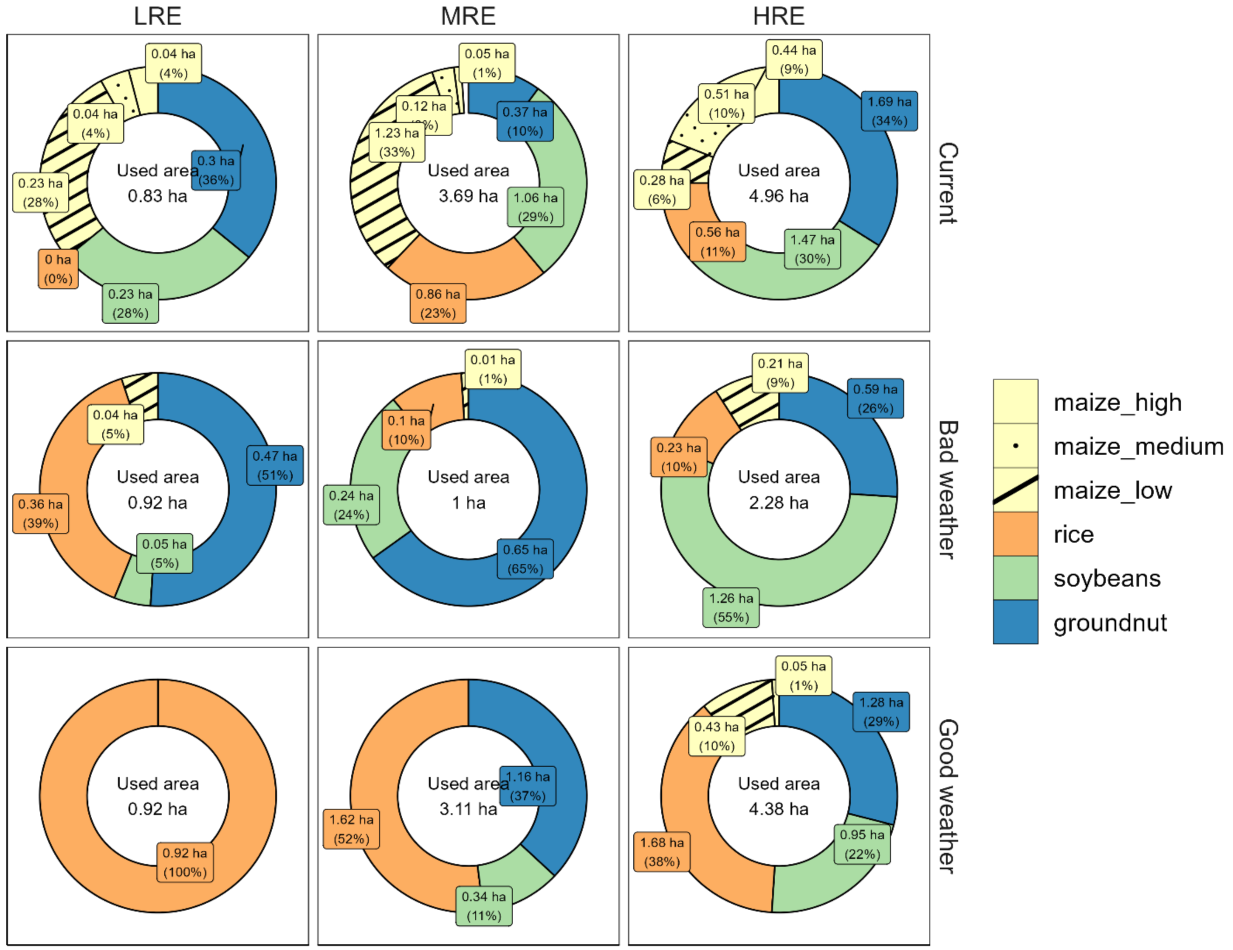

*Figure 4. Cropping patterns in the different weather scenarios. The panels at the top show the current distribution and the panel at the bottom shows the distribution in the good weather scenario. The horizontal panel in the middle shows the optimal cropping pattern in the bad weather scenario. The panels on the left represent the low-resource-endowed farms, the vertical panel in the middle represents the medium-resource-endowed farms, and the panels on the right represent the high-resource-endowed farms.*

## 4.4. Probabilities of outcomes under variable weather

The probabilities of increase in assets after five simulation years are shown in Figure 5 for the integrated model with different values of the risk aversion coefficient. The results show that in good weather scenarios and with a low-risk aversion coefficient, the probability that farmers would see their income increase over the 5-year simulation period was more than 60%. This is shown in Figure 5A–C, where the risk aversion coefficients used were 0, 0.0001, and 0.001, respectively. This means that farmers' income will likely increase, and they will be in a better position to cope with shocks if their management decisions are influenced by a model that considers the effects of risks on-farm management decisions. However, the probability of increasing income was higher under the good weather scenarios; in the bad weather scenarios, these probabilities did not fall below 50% for all farm types. If the farmers continue with their current management practices as shown in the cropping patterns highlighted above, their outputs might become much lower under the varying weather conditions since they are not responding to the climatic changes; as a result, they have a lower probability of increasing their income in both the bad and good weather scenarios. In addition, as the risk aversion coefficient increased (Figure 5E–G), there was a much lower probability that the farmers' income would increase after 5 years. This is expected since at a high risk aversion, the farmers' likelihood of perceiving a greater probability of losses increases (Menapace et al., 2013), and they tend to avoid risky investments, leading to lower incomes (Ullah et al., 2015)

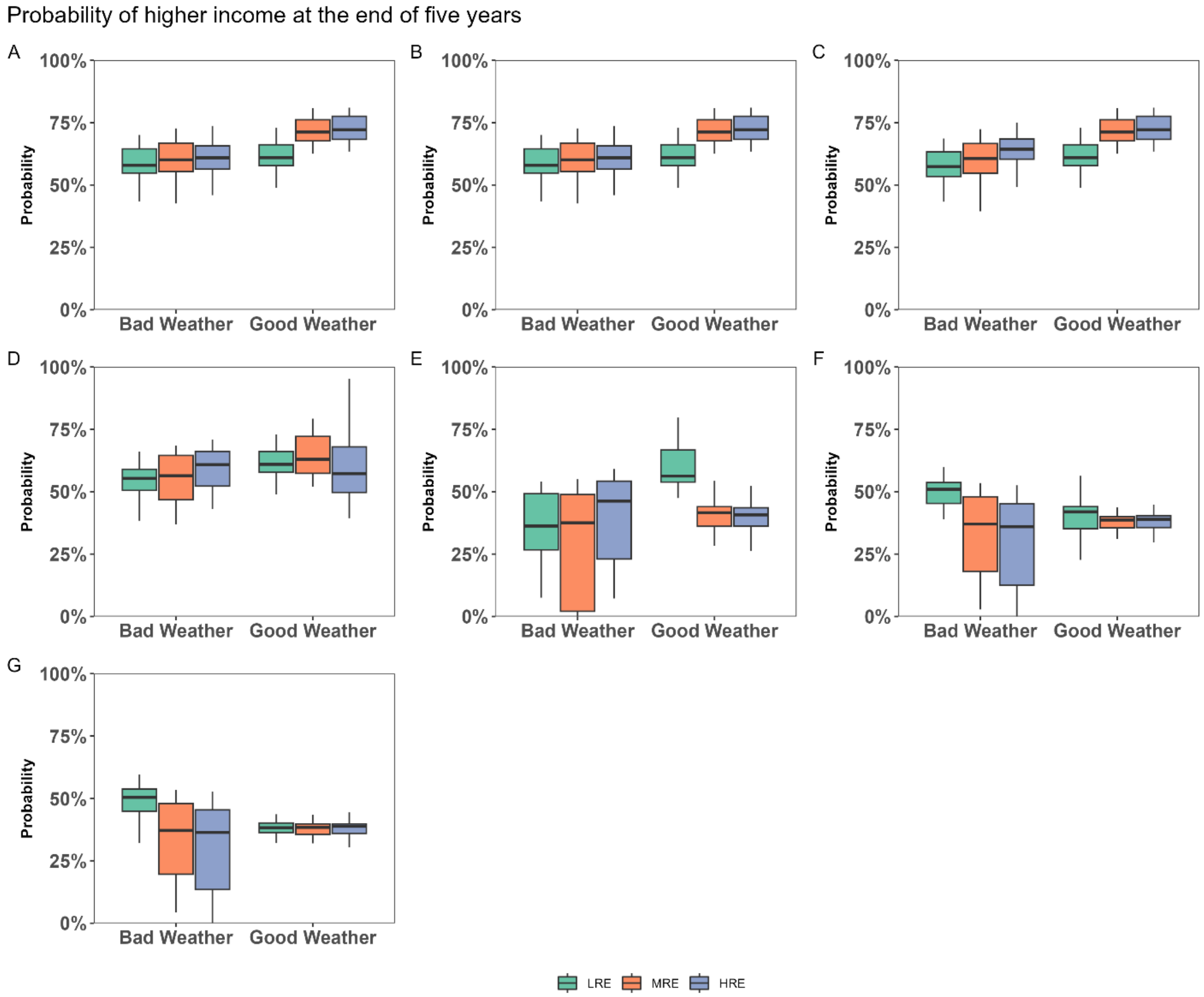

*Figure 5. Distribution of probability that farmers' income will increase over 5 years. These probabilities were obtained by comparing the average income in the first 3 years of the simulation to the last 2 years of the simulation. (A)-Simulation result with risk aversion coefficient 0; (B)-risk aversion coefficient = 0.0001;*

*(C)-risk aversion coefficient = 0.001; (D)-risk aversion coefficient = 0.01; (E)-risk aversion coefficient = 0.1; (F)-risk aversion coefficient = 1, (G)-risk aversion coefficient = 4.*

For both the integrated model and CLEM, most of the livestock was sold at the beginning of the simulation to enable the farm households to meet their consumption needs. In the subsequent years, few livestock were sold. This was expected because, during the data collection process and subsequent discussions with experts from the study area, it was observed that farmers usually run out of cash after planting and before harvest. During these periods, they meet their needs by borrowing. The models therefore sold most of the livestock at the beginning of the simulation to cover the households' minimum expenses. This is reflected in Figure 6, where all the farm households have about a 50% probability of a smaller herd size at the end of 5 years.

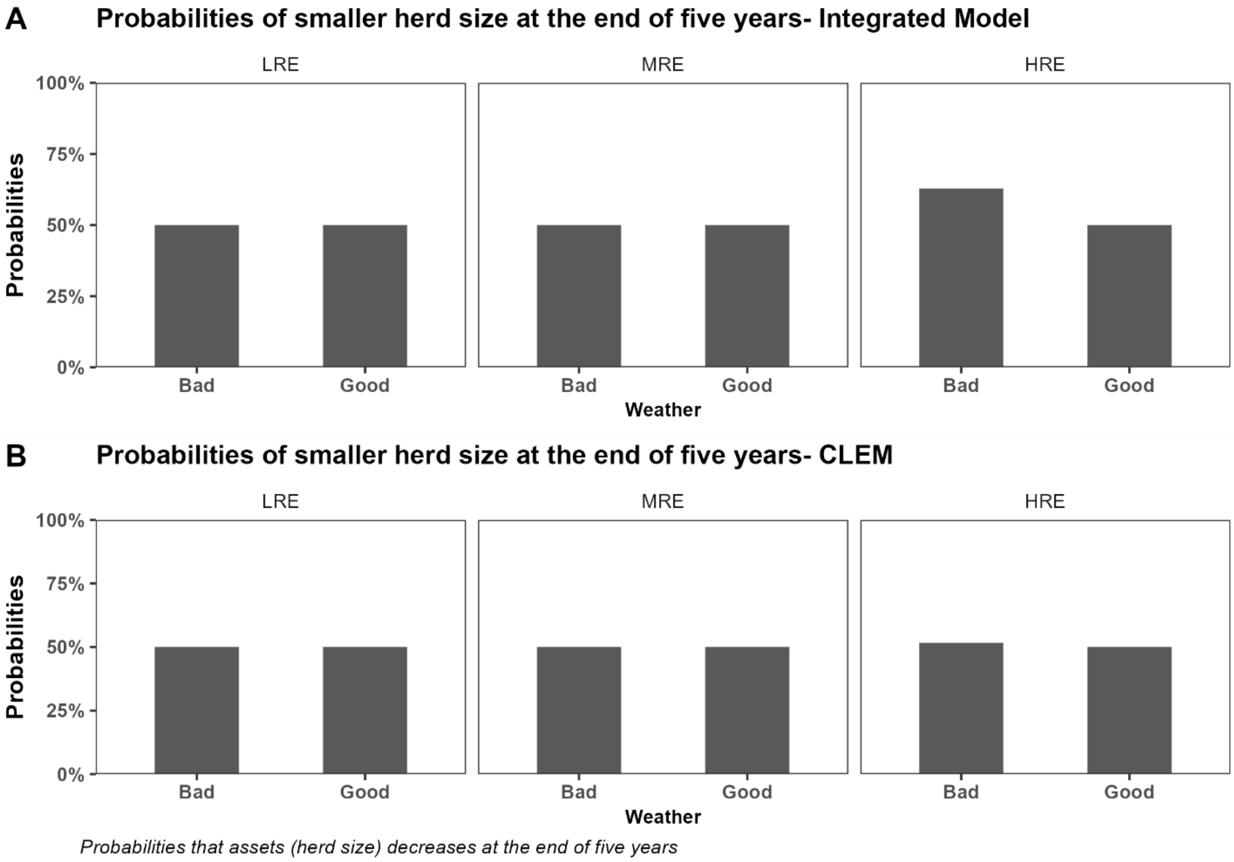

*Figure 6. Probability of smaller herd size at the end of five years. Results were obtained by comparing the average herd size after accounting for the first initial sales (at the beginning of the simulation) to the average herd size at the end of the simulation. (A)— presents the result from the integrated model, while (B) — presents the result from CLEM, which is based on the current cropping patterns of the farmers.*

## 4.5. Effects of insurance and replanting on yield allocation, incomes, and assets under shock

### 4.5.1. Maize crop yield with replanting and no-replanting scenarios

The simulated maize yield with the different fertilizer intensities under replanting and no-replanting scenarios is presented in Figure 7. As expected, maize yield increased with increasing nitrogen fertilizer rates, with an average yield of 3000kg ha$^{-1}$ at the highest fertilizer level, approximately three times greater than the yield of maize without fertilizer. This is also true for the case of no-replanting, with the average yield for maize with high fertilizer intensity generally greater than the maize with low fertilizer intensity. Results from classifying the 2020 weather show that 2020 could be classified as a normal year. The relative yield (i.e., yield at a given year divided by the average yield across 2011-2020) was slightly above one. This result[2] agrees with the FAO GIEWS report (FAO, 2023), which showed that cereal production in 2020 was at an above-average level.

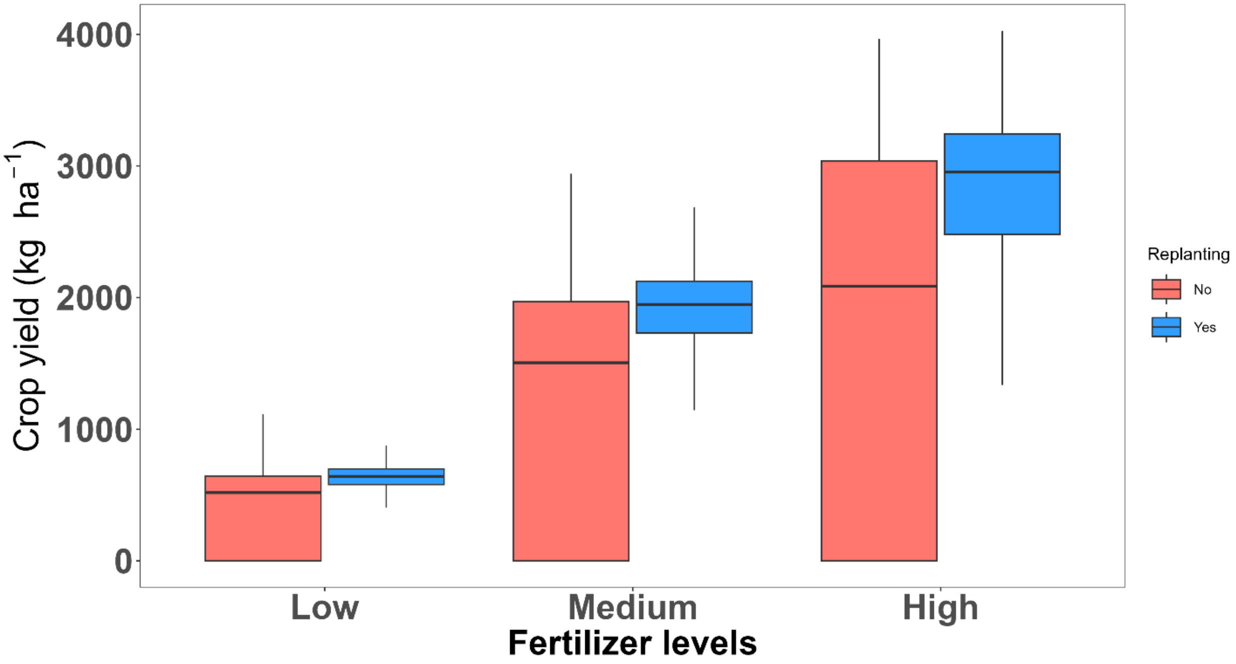

*Figure 7. Distribution of maize grain yield across fertilizer levels and with and without replanting. The red boxplots represent crop yield from no-replanting scenarios and the blue represents the yield from replanting scenarios. The horizontal line in the middle of the boxplot shows the median and the upper and lower lines show the interquartile range. The whiskers span from the edge of the box to the furthest data point within 1.5 times the interquartile range below it.*

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[2] Note that all the previous simulations were carried out using the climate model outputs (i.e., weather realisations under present-day climate conditions), not observed data.

### 4.5.2. The insurance contracts

The premium and the average indemnities for the insurance contract are presented in Table 8. Seed insurance is relatively inexpensive as farmers are required to pay less than 30 GHS ha$^{-1}$, while full insurance costs about 113 GHS ha$^{-1}$. The indemnity payment for the seed insurance is 161 GHS ha$^{-1}$ as payments are not partial but full regardless of the degree of crop failure. On the other hand, full insurance cover can pay indemnities as low as 37 GHS ha$^{-1}$ in some cases and other cases pay as high as 600 GHS ha$^{-1}$ depending on the degree of damages.

*Table 8: Premium and average indemnity payments for weather-index insurance contracts*

| Crop | Insurance cover | Growth phase | Premium (GHS ha$^{-1}$) | indemnity payments (GHS ha$^{-1}$) | | |
|---|---|---|---|---|---|---|
| | | | | Minimum[1] | Average[2] | Maximum[3] |
| Maize | Seed insurance | Germination | 28.8 | NA | 161.7 | NA |
| | Full insurance | Germination | 113.4 | 9.6 | 40.4 | 78.0 |
| | | Vegetative | | 21.7 | 100.2 | 454.8 |
| | | Flowering | | 5.9 | 19.4 | 76.2 |
| | | Pre-harvest | | 0 | 0 | 0 |
| | Total | | 113.4 | 37.2 | 160.0 | 609.0 |

*[1] Minimum non-zero indemnity payments overall weather ensemble and years*
*[2] Average non-zero indemnity payments overall weather ensemble and years*
*[3] Maximum indemnity payments overall weather ensemble and years*

### 4.5.3. Effects of insurance and replanting scenarios on farm income and assets under shock

To observe the effects of insurance options on farmers' income and how they protect farm assets, particularly in times of shocks, one representative 5-year time series was identified. In this time series, low maize yields were simulated in years with low growing season rainfall. The effects of insurance options and replanting scenarios on farmers' income and assets are presented in Figures 8 and 9. The annual farm income and assets represented in Figures 8 and 9 are the annual gross margins and farm assets (livestock and cash at hand) obtained from simulating the optimised cropping pattern with the farm management activities in the simulation model (CLEM). In Figure 8, for both MRE and HRE farms, with relatively larger farm sizes and more capital, full insurance leads to lower gross margins when weather conditions do not cause large yield losses. For these farms, in years with low yields due to drought conditions (year 4), full insurance increases farm income compared to seed and no insurance options. For LRE farms with relatively small farm sizes, the effects of insurance are not big enough because they only purchase small-size insurance contracts. As expected, in years 1 to 3 where there were no shocks, full insurance options were relatively more expensive for all the farm types compared to seed insurance and no insurance options. This is because the farmers pay a relatively high premium without getting payouts, which reduces their incomes.

In the case of replanting (Fig. 8), both insurance options are more beneficial for the farmers during shocks (i.e., year 4) as farmers' incomes increase more than without insurance options. During these periods, indemnities are paid to cover the losses and farmers are better off by purchasing insurance options. However, it is economically more beneficial for the farmers to purchase seed insurance that enables them to replant than to purchase full insurance. This is because in the event of crop failures, seed insurance is not paid partially but in full regardless of the degree of the failure whereas for full insurance, indemnities are paid according to the degree of losses at every stage. While seed insurance might pay higher indemnities in times of crop failure, they also have much lower premiums compared to the full insurance options. In addition, in some cases of extreme shocks, farmers might be unable to replant even if they want to due to insufficient capital. This case might arise due to a lack of insurance, leading to the inability of the farmer to either continue farming or meet their household needs. This can be observed with the MRE and HRE farms without insurance options recording extremely high losses during the shock years.

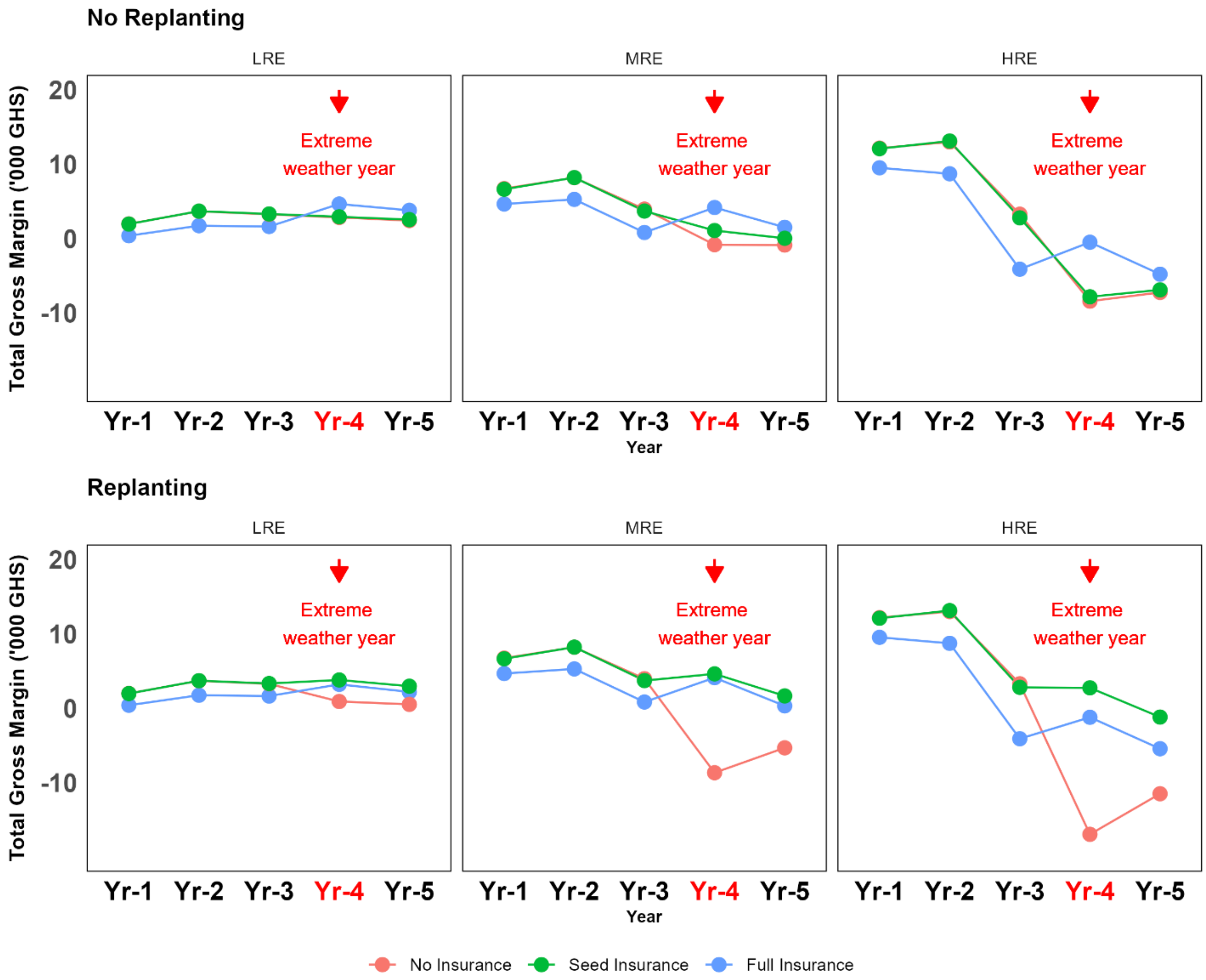

*Figure 8. Time series of gross margins under extreme weather conditions. The panels in the top row represent the no-replanting scenarios, while the panels in the bottom row represent the replanting scenarios. The left panels are for the low resource-endowed farms (LRE), the middle panels are for the medium resource-endowed farms (MRE) and the right panels are for the high resource-endowed farms (HRE). The red lines are for no insurance, the green lines are for the seed insurance and the blue lines are for the full insurance case. The red labels on the x-axis represent years with shocks, while the black labels represent years without shocks.*

Figure 9 also shows that in the case of shocks, insurance options preserve farmers' assets better than no insurance options. This is because the farmers are likely to receive compensation from insurance when a shock occurs and they can use such compensation to either meet household needs or replant for more yield, thereby reducing the need for them to sell their assets. However, full insurance options are expensive when there are no shocks (Fig. 9).

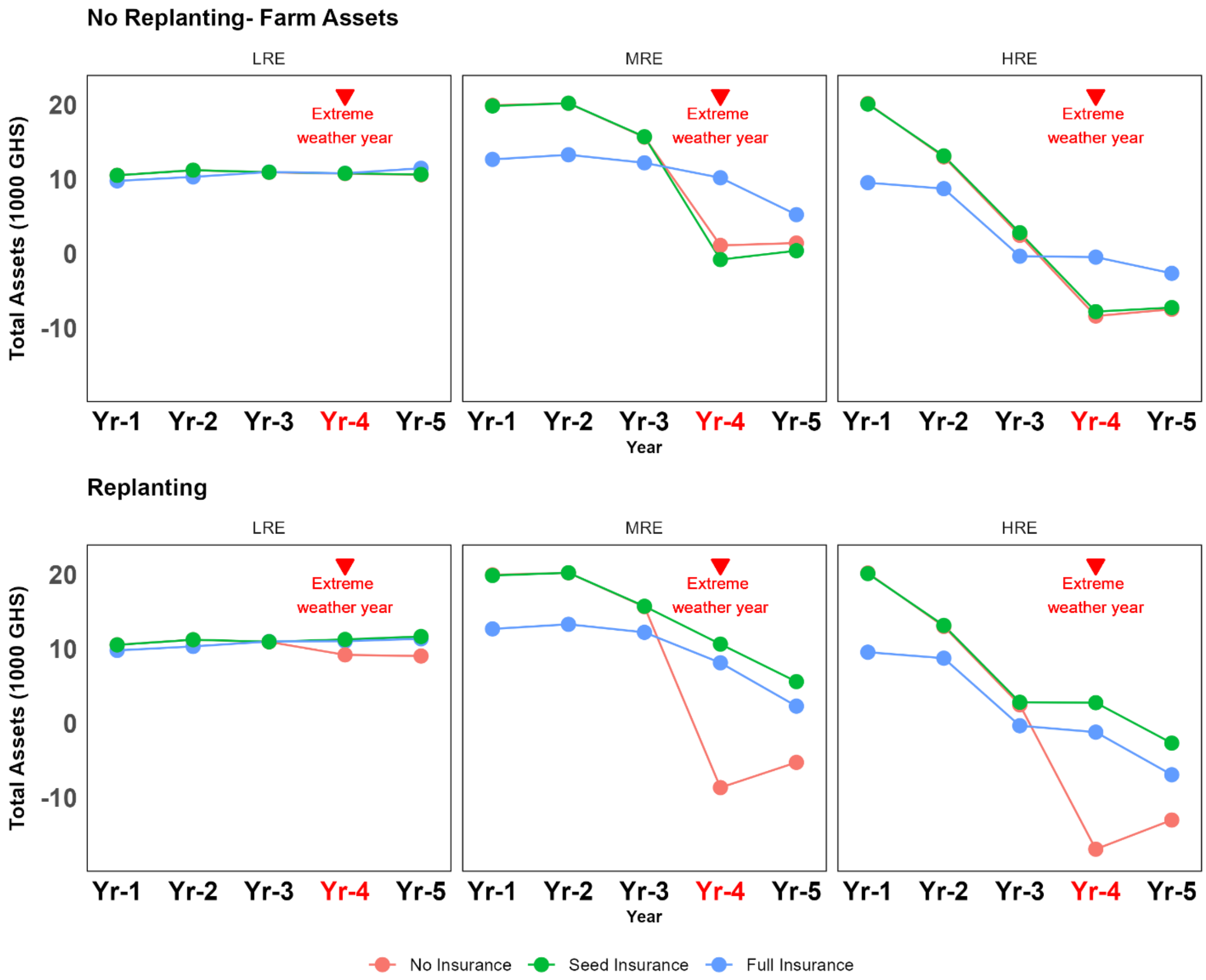

*Figure 9. Time series of total farm assets in response to different insurance and replanting options. The panels in the top row represent the no-replanting scenarios, while those in the bottom row represent the replanting scenarios. The left panels are for the low resource endowed farms, the middle panels are for the medium resource endowed farms and the right panels are for the high resource endowed farms. The green lines are for no insurance, the red lines are for the seed insurance and the blue lines are for the full insurance case. The red labels on the x-axis represent years with shocks, while the black labels represent years without shocks.*

### 4.5.4. Insurance and land allocation after a shock

To explore the effects of the different insurance options on optimal farmer's decision making and resulting allocation to different cropping activities, as in Section 4.5.3, the same 5-year time series was used. The response of the integrated model for cropping allocation patterns in the year following low maize yields and the year following high maize yields is shown in Figure 10. Results from Figure 10 show that following a normal weather year (for maize productivity), relatively smaller farms (LRE and MRE farms) allocate about 25% of their land to maize with low fertilizer intensity in all the insurance options. However, following a bad weather year, with insurance contracts (seed and full insurance options), these farms reallocate their land area to cultivate maize with higher fertilizer intensities. This is the case for LRE and MRE farms allocating about 40% and 30% of their land area to maize with medium and high fertilizer intensity, respectively. For the relatively larger farms i.e., HRE farms, in the year following normal weather conditions, they cultivate an equal proportion of maize fertilizer intensities (low, medium, and high) with less than 20% of their land area in all the insurance options. However, in a year following the climate shock, they increased the proportion of land area allocated to maize to about 30% of their land area, allocating more than 25% of that to maize with high fertilizer intensity. The farms simulated here generally increase their land area allocated to maize after a bad growing season to meet their household maize requirements. As shown with the results from a single weather time series, insurance plays a very vital role in stabilising farmers' income in shock years, it is worth noting that these shock years do not occur regularly.

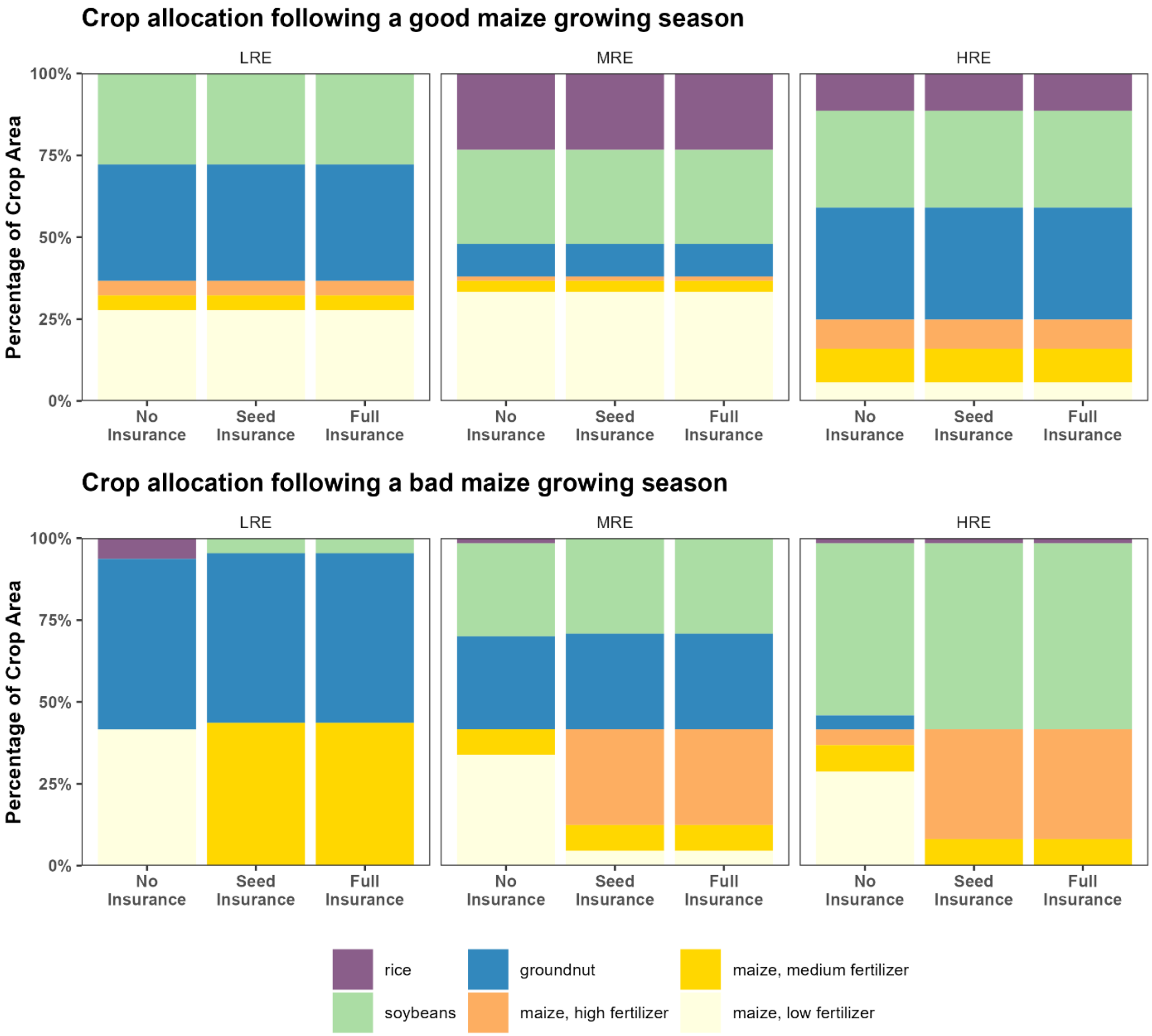

*Figure 10. Cropping activities under different insurance options and replanting scenarios. The panel in the top row represents the results following a good maize growing season. The panel in the bottom row represents the results following a bad maize growing season (after a shock year). The left panels are for the low resource-endowed farms (LRE), the middle panels are for the medium resource-endowed farms (MRE) and the right panels are for the high resource-endowed farms (HRE). The purple colour in the bar plot represents the land allocation to rice crops, the blue colour shows the land allocation to groundnut, the green colour shows the land allocation to soybeans, the orange colour shows the land allocation to maize crops with high fertilizer rates, the yellow colour shows land allocation to maize crop with medium fertilizer rates, and the light-yellow colour shows the land allocation to maize with low fertilizer application.*

## 4.6. Effects of insurance and replanting scenario on income and farm assets

The effects of insurance options and the replanting scenarios on annual household farm income were assessed by exploring the probability of farm income increasing after 5 years for the full 400-climate ensemble weather data as presented in Figure 11. The income in the second year (year 2) of the simulation was compared to the income of the last year of the simulation (year 5). The first year of the simulation was excluded from the probability calculation to remove the effects of optimisation on farm income. Figure 11 shows that on average, considering all the possible weather conditions, seed and full insurance options do not significantly increase farmers' average income compared to a case of no insurance. This is shown in Figure 11, where the farm households have a chance of about 40% of increasing their income after 5 years in the no-replanting scenario. This is understandable considering that these insurance options only pay the farmers in extreme cases, which rarely occurs. This will most likely reduce their income as they pay more than they get on average. This is also the case for the replanting scenario, where the farm households have about a 50% probability of increasing their farm income after 5 years in all the 3 insurance options.

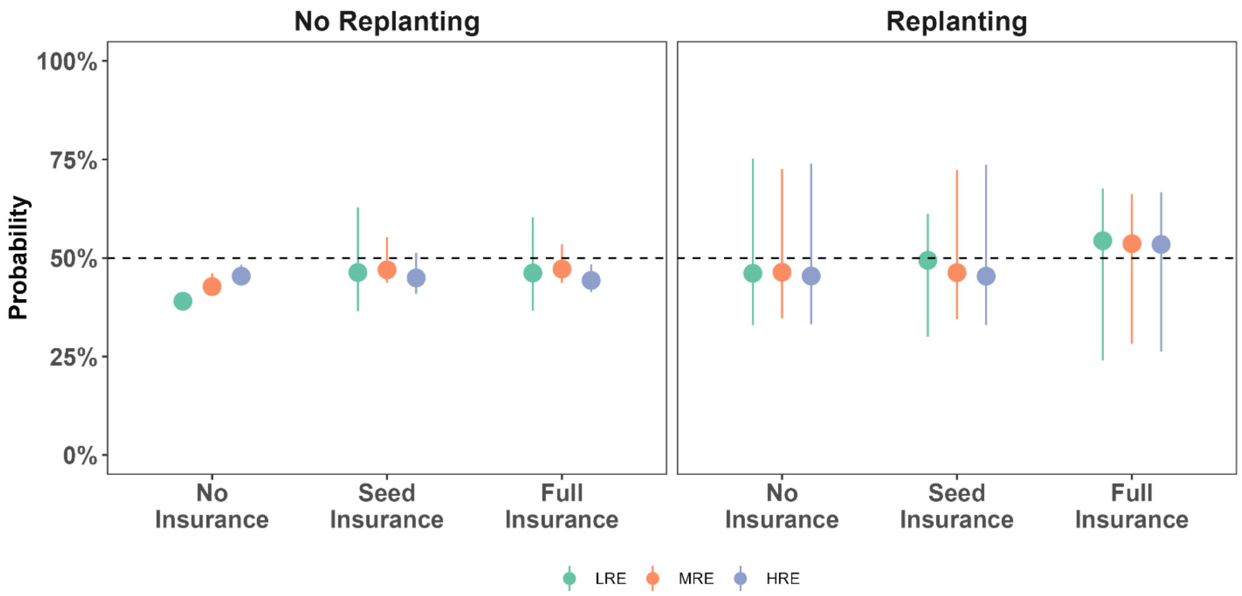

*Figure 11. The probability that farm income increases after 5 years for different insurance products and replanting scenarios. The probability is obtained by comparing the income in year 2 of the simulation to the income in year 5 of the simulation. The panels on the left are the results from the no-replanting scenario; The panels on the right are the results from the replanting scenario. The green point range represents the LRE farms, the orange represents the MRE farms, and the blue represents the HRE farms. The lower and upper lines extending from the points show the minimum and maximum probabilities, respectively. The horizontal dash line shows the 50% probability line. LRE farms are Low Resource Endowed Farms, MRE farms are Medium Resource Endowed Farms and HRE farms are High Resource Endowed Farms*

As herd size is a form of liquid asset important for dealing with shocks (Breckner, 1958; Siegmund-Schultze et al., 2007), the monetary value of the available livestock was combined with the cash at hand to determine the effects of WII on farm assets. The probability that farm assets increase after 5 years with different insurance products and replanting scenarios is shown in Figure 12. On average, farm assets are likely to decrease after 5 years, and the outcomes are similar for the different insurance options and replanting scenarios with about a 25% to 30% probability that farm assets will increase in all the scenarios. While replanting offers a slightly less negative outlook on the chance of reducing asset loss with an insurance product, it is still not likely that farmers avoid asset losses. Assets are still likely to decrease even with WII, reflecting the costs for premiums to be paid in all good and bad years, while payouts are only in bad years.

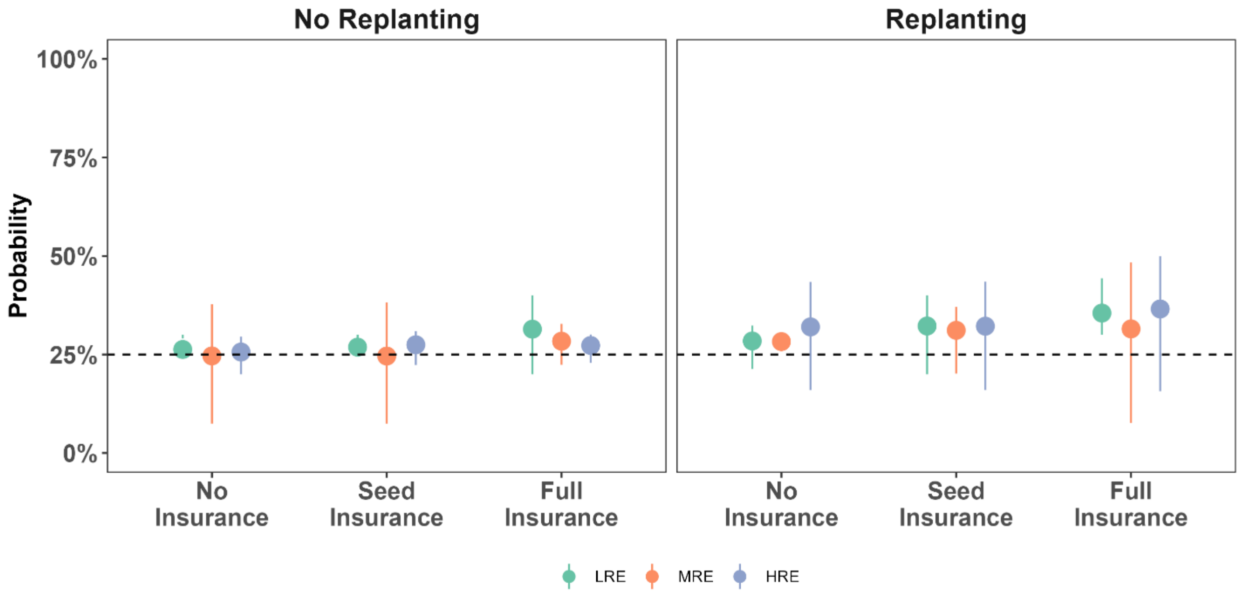

*Figure 12**.** The probability of farm assets increases after 5 years with different WII products and replanting scenarios. Farm assets are defined by the sum of the cash value of the herd (small and large ruminants) and cash at hand. The probability compared the farm asset at year 2 of the simulation to the farm asset at the end of the simulation (year 5). The panel on the left shows the no-replanting scenario and the panel on the right shows the replanting scenario. The green point range represents the LRE farms, the orange represents the MRE farms, and the blue represents the HRE farms. The lower and upper lines extending from the points show the minimum and maximum probabilities, respectively. The horizontal dash line shows the 25% probability line. LRE farms refer to Low Resource Endowed Farms, MRE farms refer to Medium Resource Endowed Farms and HRE farms refer to High Resource Endowed Farms*

## 4.7. Effects of basis risk on the effectiveness of WII

The results in the previous sections have assumed a perfect design of the WII product. In fact, the effectiveness of WII depends on the design of the insurance contracts. A faulty insurance contract design can overestimate or underestimate the potential losses of the farmers under extreme events. To explore the importance of different sources of basis risk, yield, gross margins, and farm assets are compared under the different basis scenarios in the following sections.

### 4.7.1. Crop yield distribution with basis risk

Crop yield for maize under different fertilizer application intensities and different scenarios are presented in Figure 13. The ecological and biophysical parameters have a large influence on crop yield (Fig. 13), this is well-known based on crops' response to weather, soil water and nutrient availability (Ewert et al., 2015). In the figure, delaying the planting date by up to 21 days (PD+21) led to a large reduction in yield across the full ensemble of weather conditions, where the crop yield for maize with medium and high fertilizer intensity is less than the reference yield (representing the conditions assumed as representative of growing conditions) value by over 1000kg ha$^{-1}$. This is also the case with soil depths 30cm lower than the reference soil depths (SD-30), where crop yield was lower than the reference yield by about 2000kg ha$^{-1}$. In addition, it can also be observed that the median yield for SD-30 is relatively lower across all fertilizer intensity levels.

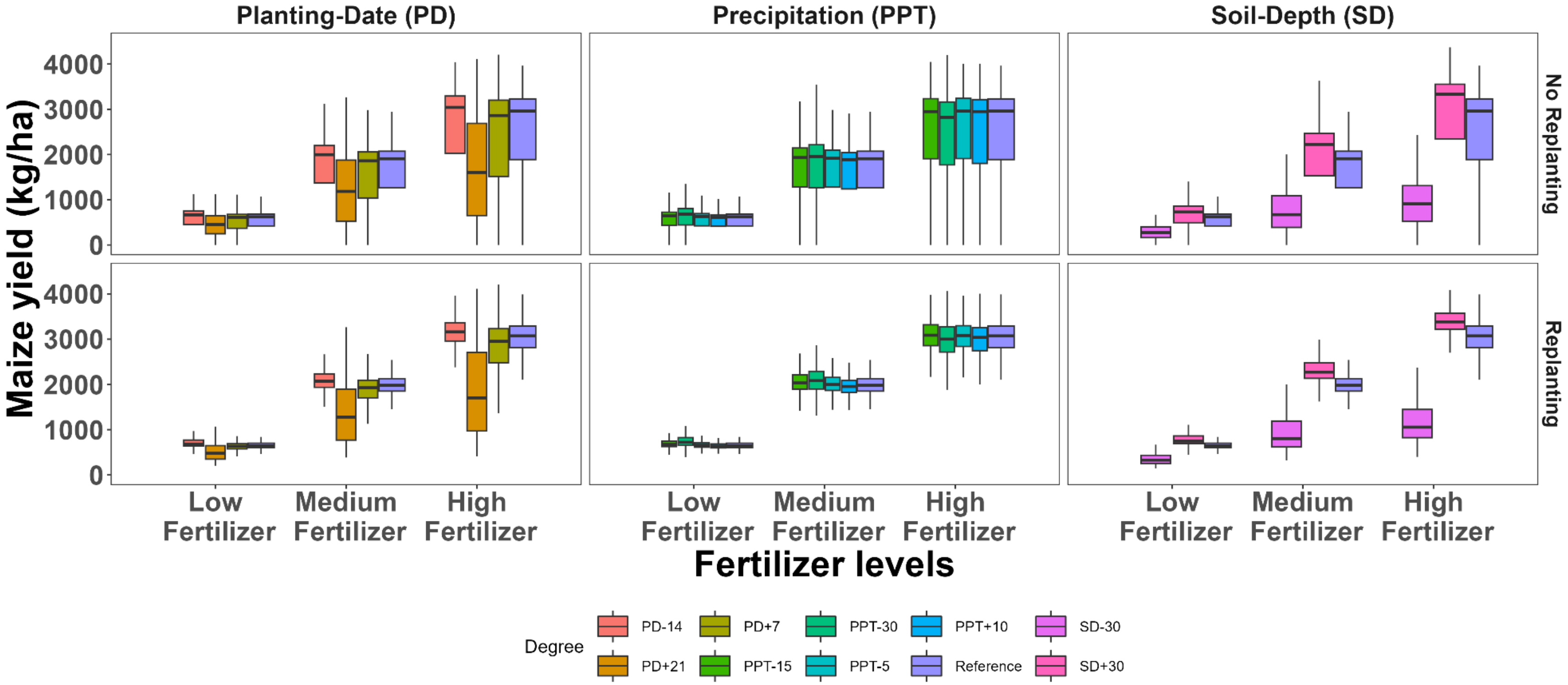

*Figure 13: Crop yield distribution under differing basis risk scenarios. The panels in the top row show simulations with the no-replanting scenarios. The panels in the bottom row represent the simulations with replanting scenarios. The panels in the first (left) column show simulations with different planting date scenarios. The panels in the middle column show the simulations with the precipitation scenarios and the panels in the third column show the simulations with the soil depth scenarios. Each box plot indicates the yield with uncertainty across the ensemble of all weather conditions. Reference represents the conditions assumed as representative of growing conditions. PD-14 represents the scenario for planting 14 days earlier than the reference date. PD+21 represents the scenario for planting 21 days later than the reference date. PD+7 represents the scenario for planting 7 days after the reference date. PPT-15 represents a scenario for precipitation 15% lower than the reference precipitation. PPT-30 represents a scenario for precipitation 30% lower than the reference precipitation. PPT-5 represents a scenario for precipitation 5% lower than the reference precipitation. PPT+10 represents the scenario for precipitation 10% higher than the reference precipitation. SD+30 represents the scenario for a soil depth 30cm higher than the reference soil depth. SD-30 represents a scenario for a soil depth 30cm lower than the reference soil depth. The horizontal lines in the middle of the boxplots show the median and the upper and lower lines show the interquartile range. The whiskers span from the edge of the box to the furthest data point within 1.5 times the interquartile range below it.*

### 4.7.2. Basis risk and the effect of WII in increasing farm margins and assets in a year following an extreme weather event

In the following, we discuss the effects of various sources of basis risk on farm gross margins and assets for the case of replanting after a yield failure for the case of MRE farms. As presented in figures 14 and 15, with the case of WII, assumptions that deviate from the representative growing conditions (i.e., reference conditions) can lead to overestimating or underestimating farmers' losses in the event of climate shocks, thereby increasing or decreasing their potential indemnity payments. From the results, gross margins and farm assets steadily rise until when farmers experience a climate shock (i.e., year). In this year, gross margins and farm assets respond based on the insurance options. When there is no insurance to cushion the effects of climate shocks, the gross margins and farm assets fall quickly. With insurance options (i.e., seed or full insurance), the gross margins and farm assets are stabilized. However, the issue of basis risk can be observed from the results as both gross margin and farm assets respond differently under different assumptions. Temporal basis risk can reduce the farmers' compensation during shock if the insurance contract is designed with a planting date that is at least 7 days later than the reference date (PD+7) (Fig. 14). The indemnity paid to the farmers in year 4 under PD+7 is lower than the reference. On the other hand, faulty design arising from earlier planting dates can lead to compensation beyond farmers' real losses and overpayments by the insurance company, for PD-14 as compared to the reference planting date. Overpayment of indemnities is highest in the event of product basis risk, where the actual soil depth of the farmers' field was increased to 30cm, while underpayment is highest when the soil depth at the farmers' field is 30cm lower than the one used for index calculation (reference soil depth) (Fig. 14). This effect is also seen on farmers' assets (Fig. 15), where overpayments and underpayments of indemnity are highest in the case where the soil depth is 30cm lower and 30cm higher than the actual farm depth, respectively. In addition, it can be observed that with higher precipitation compared to the reference precipitation (PPT+10), gross margins and farm assets decrease under both normal and extreme weather conditions (Fig. 14 and 15).

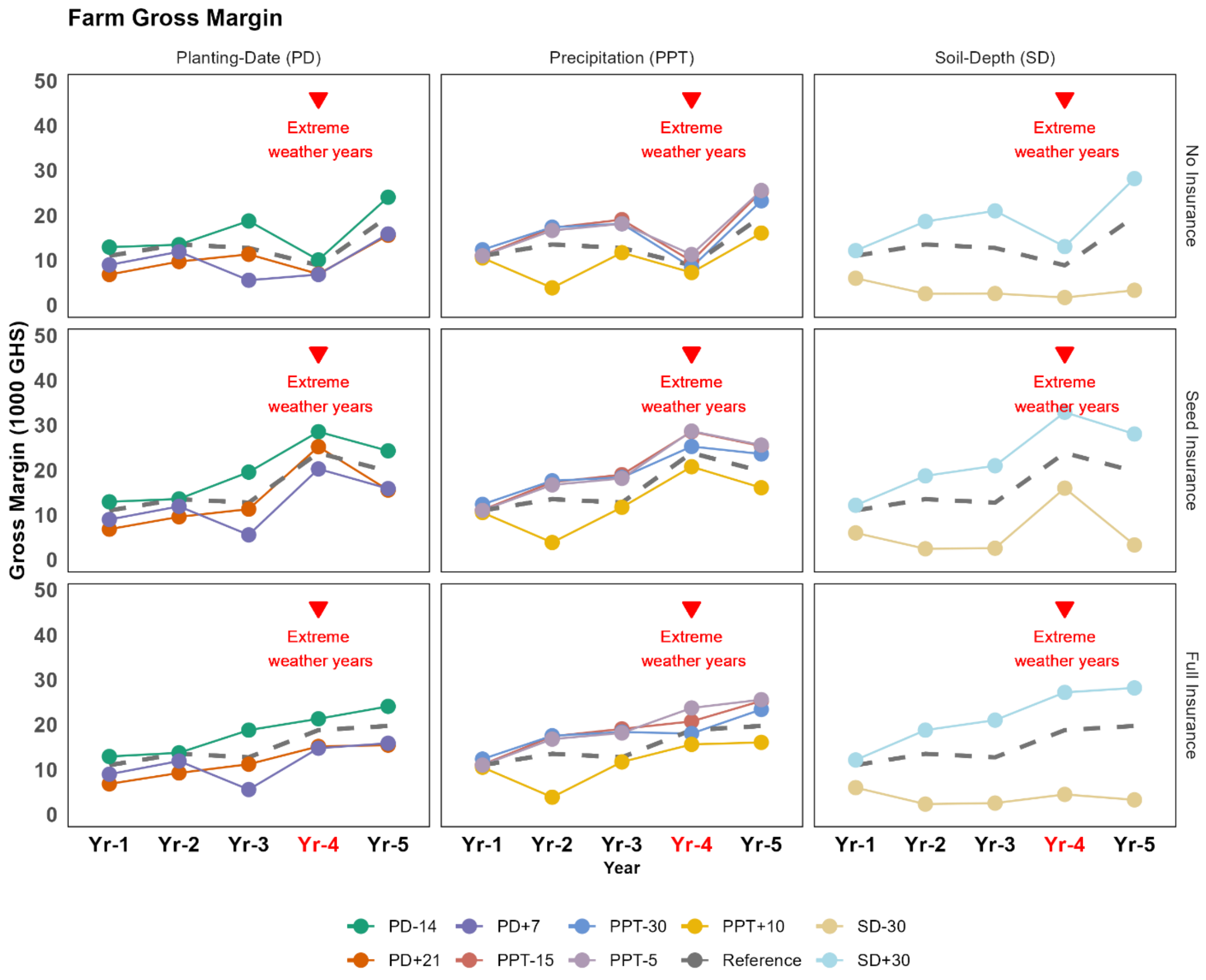

*Figure 14: Time-series of gross margins with different scenarios where the 4th year is an extreme weather year resulting in effects on simulated maize yields assuming replanting if maize did not emerge. The panels in the top row are for simulations without insurance. The panels in the middle row show the simulations with the seed insurance option while panels in the bottom row show the simulations with the full insurance options. The panels in the first (left) column contain the planting date scenarios, the panels in the middle column show simulations with the precipitation scenarios and the panels in the third (last) column show the simulations with the soil depth scenarios. The black dash line shows the reference for all scenarios, which represent the conditions assumed as representative of growing conditions. The green line (PD-14) represents the scenario for planting 14 days earlier than the reference date. The dark red line (PD+21) represents the scenario for planting 21 days later than the reference date. The dark blue line (PD+7) represents the scenario for planting 7 days later than the reference date. The light red line (PPT-15) represents the scenario for precipitation 15% lower than the reference precipitation. The light blue line (PPT-30) represents the scenario for precipitation 30% lower than the reference precipitation. The purple line (PPT-5) represents the scenario for precipitation 5% lower than the reference precipitation. The dark orange line (PPT+10) represents the scenario for precipitation 10% higher than the reference precipitation. The light purple line (SD+30) represents the scenario for soil depth 30cm higher than the reference soil depth. The light orange line (SD-30) represents the scenario for soil depth 30cm lower than the reference soil depth*

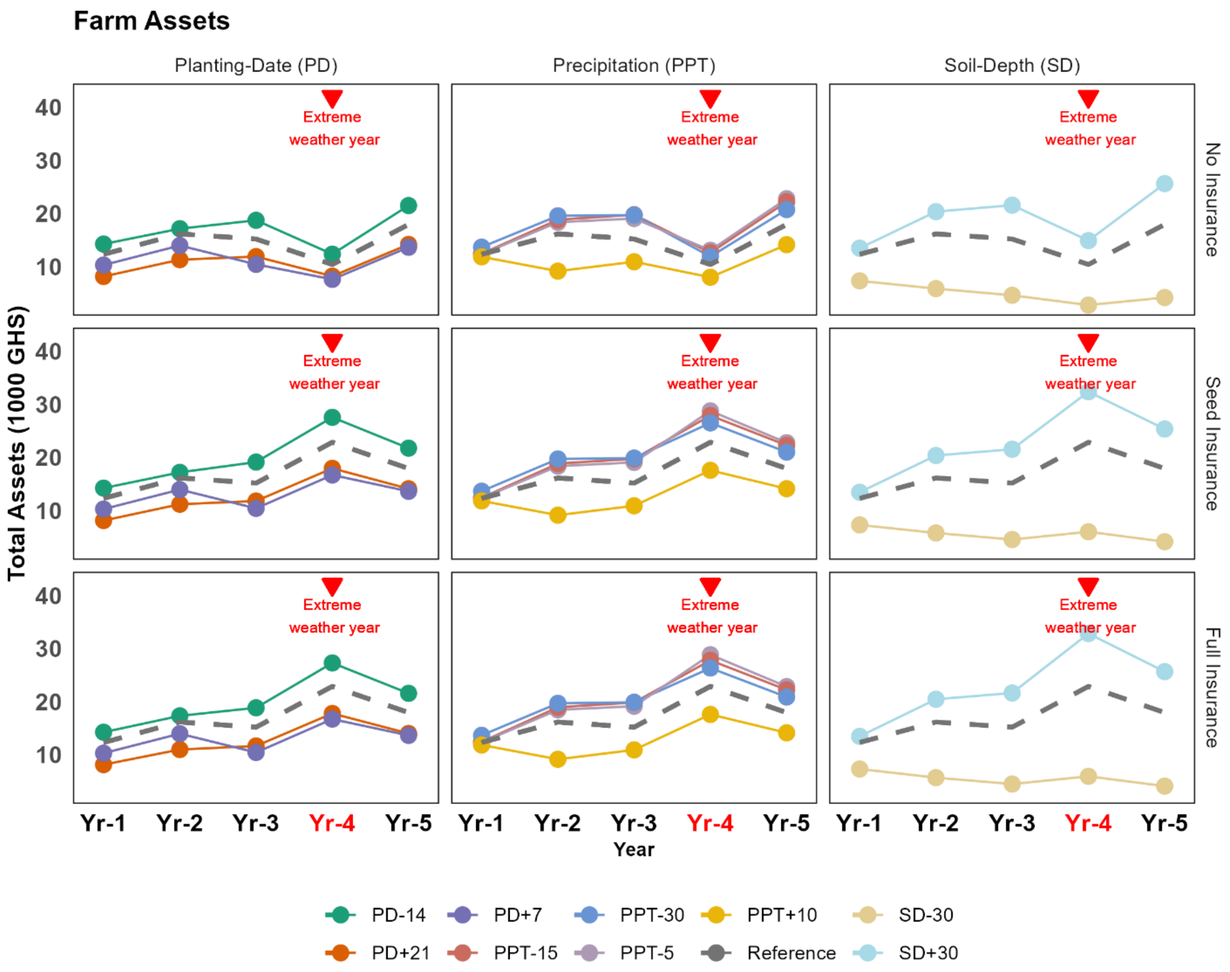

*Figure 15: Time-series of farm assets with different scenarios where the 4th year is an extreme weather year resulting as determined by effects on simulated maize yields assuming replanting if maize did not emerge. The panels in the top row are for simulations without insurance. The panels in the middle row show the simulations with the seed insurance option while panels in the bottom row show the simulations with the full insurance options. The panels in the first (left) column contain the planting date scenarios, the panels in the middle column show simulations with the precipitation scenarios and the panels in the third (last) column show the simulations with the soil depth scenarios. The black dash line shows the reference for all scenarios, which represent the conditions assumed as representative of growing conditions. The green line (PD-14) represents the scenario for planting 14 days earlier than the reference date. The dark red line (PD+21) represents the scenario for planting 21 days later than the reference date. The dark blue line (PD+7) represents the scenario for planting 7 days later than the reference date. The light red line (PPT-15) represents the scenario for precipitation 15% lower than the reference precipitation. The light blue line (PPT-30) represents the scenario for precipitation 30% lower than the reference precipitation. The purple line (PPT-5) represents the scenario for precipitation 5% lower than the reference precipitation. The dark orange line (PPT+10) represents the scenario for precipitation 10% higher than the reference precipitation. The light purple line (SD+30) represents the scenario for a soil depth 30cm higher than the reference soil depth. The light orange line (SD-30) represents the scenario for a soil depth 30cm lower than the reference soil depth.*

### 4.8. How basis risk affects the probability of improved incomes and assets across different weather conditions

To examine the effects of basis risk on long-term farm income, the probability that farm income increases after 5 years was explored for the full 400-member ensemble weather data for all cases of basis risk (Fig. 16). Farmers have a much lower probability of increasing their farm income with a poorly designed insurance option that is based on a soil depth that is 30cm lower than actual soil depth of the farmers' field. The probability of increasing farm income after 5 years under SD-30 is about 50%, which is much less than the probability of the other sources of basis risk. For the other scenarios, there was no strong effect of lower incomes after 5 years, although such tendencies can be seen in PPT-30 and PD-14 (Fig. 16)

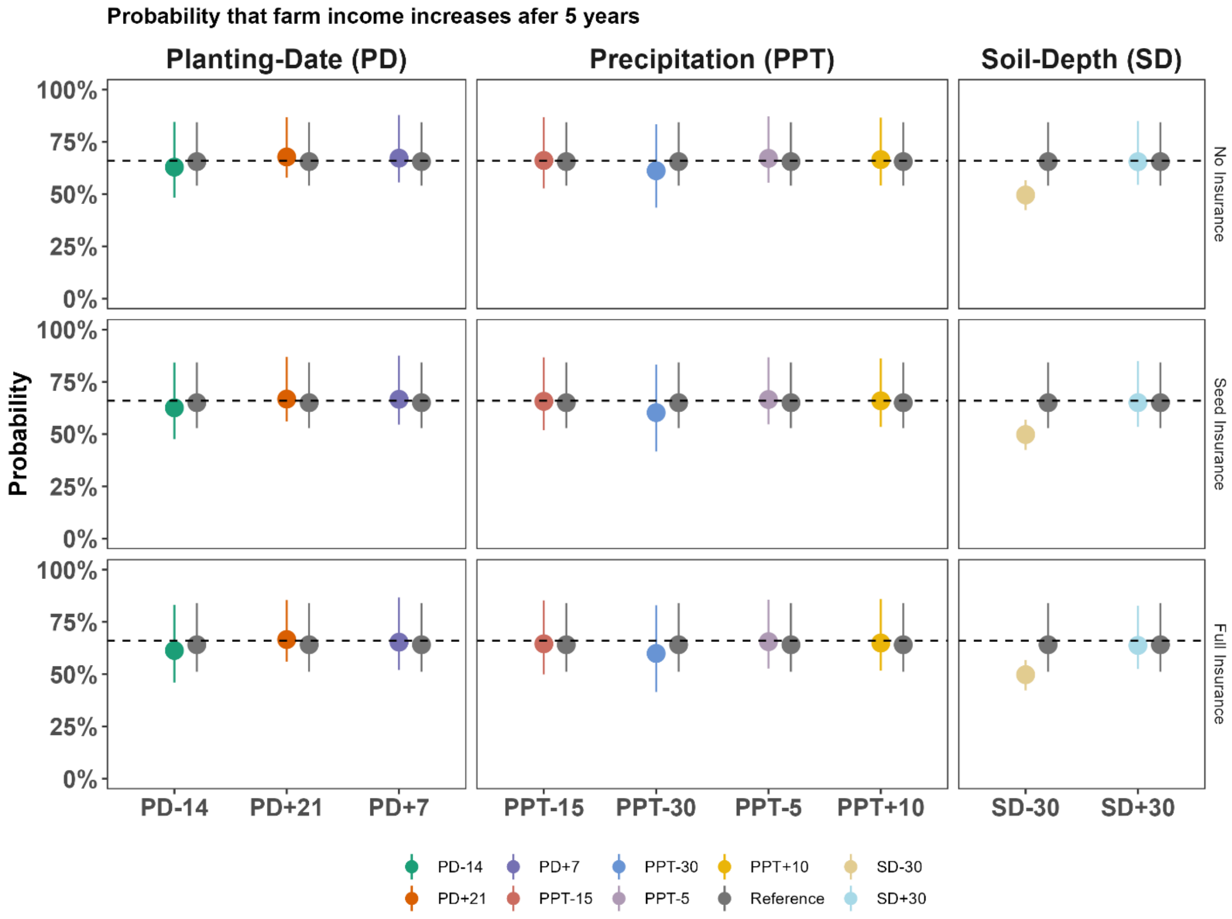

*Figure 16: Probability of increase in farm income after 5 years under different scenarios. The probability was obtained by comparing the income in year 2 of the simulation to the income in year 5 of the simulation. The panels in the top row are for simulations without insurance. The panels in the middle row show the simulations with the seed insurance option while panels in the bottom row show the simulations with the full insurance options. The panels in the first (left) column contain the planting date scenarios, the panels in the middle column show simulations with the precipitation scenarios and the panels in the third (last) column show the simulations with the soil depth scenarios. The black dash line and the black point range*

*show the reference for all scenarios, which represent the conditions assumed as representative of growing conditions. The green point range (PD-14) represents the scenario for planting 14 days earlier than the reference date. The dark red point range (PD+21) represents scenario for planting 21 days later than the reference date. The dark blue point range (PD+7) represents the scenario for planting 7 days later than the reference date. The light red point range (PPT-15) represents than scenario for precipitation 15% lower than the reference precipitation. The light blue point range (PPT-30) represents the scenario for precipitation 30% lower than the reference precipitation. The purple point range (PPT-5) represents scenario for precipitation 5% lower than the reference precipitation. The dark orange point range (PPT+10) represents the scenario for precipitation 10% higher than the reference precipitation. The light purple point range (SD+30) represents the scenario for soil depth 30cm higher than the reference soil depth. The light orange point range (SD-30) represents the scenario for soil depth 30cm lower than the reference soil depth*

# 5. Discussion

## 5.1. Relevance of the study

Given increasingly variable and extreme weather conditions and other shocks (markets, pandemics, war), supporting the sustainable intensification of farming systems will require the consideration of how resource allocation decisions are altered and affected by shocks (Ricome et al., 2017) and what the implications are for longer-term sustainable development (Rusinamhodzi et al., 2011). Indeed, it is well known that more intensified systems are associated with higher yield variability (Faye et al., 2018; Ray et al., 2015) and larger potential losses during bad weather years (Danso et al., 2018; Hansen et al., 2019). The correct mix of risk reduction, risk transfer, and enabling prudent investments to cope with agronomic risks will differ based on the farm type (Aidoo et al., 2014; Alhassan et al., 2019; Huet et al., 2020; Laube et al., 2012), agro-ecological, market, and institutional context (Giller, 2020). It is therefore important to develop risk assessment frameworks to understand the appropriate risk management pathways to achieve sustainable intensification for these different contexts. The integrated model presented in this thesis offers a novel approach to making such assessments by considering how weather conditions affect production and, in turn, future management and investments. This was accomplished by combining farm-level optimisation and simulation models with a process-based crop modelling framework driven by large ensemble weather datasets. Like many other bio-economic farm optimisation approaches, the optimisation model presented in this thesis strongly assumes that farmers allocate resources and make production decisions to maximise their gross margins as modulated by their risk aversion characteristics. By linking our optimisation model with an annual simulation model (CLEM) that accounts for monthly resource flows, the annual optimisation approach explicitly accounts for how bad weather affects crop yields in the previous season limits cash availability and may alter subsequent cropping system management decisions.

While focused primarily on financial risk management at the farm level, The thesis explored the effectiveness of different risk management options in enabling investments in improving crop yields and incomes. By comparing the trajectories of the different scenarios, the most cost-effective and rational risk management option was identified for farmers under the diverse weather conditions encountered. In addition, the thesis provides insights into the effectiveness of different forms of WII in stabilising farmers' income under extreme weather conditions and the effect of basis risk on these insurance options. Notably, the work of Yami & Van Asten (2017) highlighted the positive effects of crop insurance on agricultural markets, credit access, and savings schemes. However, in the case of Northern Ghana, the scarcity of studies assessing the impacts of insurance on farmers' income is partly due to the absence of active index insurance options for farmers (Di Marcantonio & Kayitakire, 2017) among others. Unlike many other studies that focus on the demand and the willingness to pay for insurance products in Ghana (Adzawla et al., 2019; Afriyie-Kraft et al., 2020; Ankrah et al., 2021; Kwadz et al., 2013), the work presented here tested the impacts of specifically developed weather-index insurance products on farmers' income, evaluating the probabilities of increasing farmers' income. By examining the effects of purchasing insurance contracts and making decisions regarding replanting in the event of crop failure on farmers' income, the thesis was able to assess how these options protect farm assets, especially in extreme weather conditions, considering these factors are key motivations for farmers to purchase insurance contracts (Jensen & Barrett, 2017).

## 5.2. Probabilistic approach to evaluating climate risk and risk management outcomes

Several studies have simulated the effects of weather and other production risks on different household or farm components such as production, land degradation (Bidogeza et al., 2015; Holden & Shiferaw, 2004), farm production system (Mosnier et al., 2009), and prices and subsidies (Mouysset et al., 2011). However, the approach presented in this thesis is unique due to the application of a large ensemble of possible weather realisations as inputs for the integrated model. In plain language, this allows exploring the response of the system for a very wide range of weather for next year even if we know the climate characteristics. Exploring responses over a range of plausible weather conditions enables assessing the probability of changes in incomes or assets. This is understood as a good basis for supporting change at local levels (Hansen et al., 2022). The large ensemble simulations can help to better understand the associated climate risks for crop production (Ewert et al., 2015) as it captures a greater range of possible conditions, including more extreme weather events. According to Afshar et al. (2021), this approach helps analyse the performance of management options including the adoption of WII as the simulated yield data contains a range of potential weather and agronomic conditions.

## 5.3. Weather index-based insurance as a risk management option

Farmers' long-term income and livelihood are negatively affected by years of extreme weather conditions (Gadédjiss-Tossou et al., 2016), leading them to various undesirable behaviours such as selling assets, which leaves them worse off (Herrero et al., 2013). As a tool to relieve the burden of agro-climatic risks at the farm level (Ricome et al., 2017), WII has received wide attention for their potential as affordable measures to buffer the effects of crop failure on farmers' income (Abugri et al., 2017). Unsurprisingly, results from this study suggest that farmers are better off purchasing WII during extreme weather years. With this, the insurance covers most of their losses and the farmers do not have to resort to other means like borrowing or selling their assets during extreme weather conditions. Tadesse et al. (2015) highlighted the benefits of WII during extreme weather events and advocated for the need to design contracts based on larger shocks. Several other studies have also supported this call by stressing the importance of WII particularly in extreme weather events (Collier et al., 2009; Greatrex et al., 2015; N. Jensen & Barrett, 2017; Shirsath et al., 2019). However, this thesis underlines the reality that full WII contracts are expensive for farmers when they do not experience shocks, as seen from the single weather time series effects presented in Figures 8 and 9. This was also clearly demonstrated by Boucher et al. (2024) in East Africa. Considering the full weather distributions of current climates, our results suggest that purchasing full coverage WII leaves farmers worse off with insurance options since extreme weather events do not occur regularly, while farmers must pay premiums each year. This result is particularly important as it further emphasizes one reason for the low subscription of WII in Northern Ghana. A key informant interviewed by Ankrah et al. (2021) complained that "*insurance is a way of taking people`s money because extreme weather events do not occur regularly*".

Smallholder farmers are reluctant to purchase insurance contracts unless the premiums are subsidised or the insurance options are coupled with other benefits (Ricome et al., 2017; Sibiko et al., 2018). One more affordable option investigated in this thesis is purchasing certified seeds coupled with a seed emergence insurance product. According to Bulte et al. (2020), this has been found to increase farmers' adoption rates and incentivise them to purchase insurance products. Crops are mostly vulnerable to extreme weather conditions at the germination phase, which is known to lead to a high incidence of crop losses (Bulte et al., 2020; Li & Miranda, 2015). However, a resource-constrained smallholder farmer may be unable to re-purchase seeds and other inputs for replanting after a crop failure (Li & Miranda, 2015). Our results suggest that replanting is more feasible with the purchase of WII covering seed and associated costs (Fisher et al., 2019; World Bank, 2015), as farmers pay much lower premium rates in good years and can prevent catastrophic income losses by avoiding yield failures associated with early drought stress. Results in this thesis show that the seed WII enables farmers to replant and stabilise their incomes in the event of crop failure during early extreme weather events, which might not be economically possible for them without insurance. This outcome is supported by Fisher et al. (2019), who highlighted that replanting after crop failure can potentially increase liquidity.

Many studies have examined the willingness to pay for WII by different smallholding farming households, highlighting that farmers' reluctance to pay for these products is due to high prices (Binswanger-Mkhize, 2012; Vasco et al., 2008). ShalekBriski et al. (2021) highlight that WII is less expensive than indemnity-based insurance as it reduces administrative costs. However, as seen with the contracts presented in this thesis, full WII cover is often too expensive for low-income earning farmers as in many cases they pay more than they benefit. Farmers might be unwilling to take up insurance contracts because they might not get "the benefits" for several years due to a series of good weather years (Boucher et al., 2024). With an average cost of 113 GHS ha$^{-1}$ (Table 8), high prices of insurance contracts are one of the reasons for farmers' low subscriptions in Northern Ghana. A good alternative is the weather index seed insurance option presented in this thesis, which can enable farmers to replant in times of extreme weather conditions. These insurance contracts are relatively cheaper (about 28 GHS ha$^{-1}$) as they do not cover the full growing phase of the crops, and the payouts are fixed regardless of the degree of crop failure. Such insurance products have been reported to be successfully implemented in Tanzania, covering about 30,000 people in 2018 (Simões, 2021). Considering the costs of the two insurance types, promoting weather index seed insurance could be an effective strategy for increasing the subscription rates of insurance in the region since price plays a very important role in the demand for index insurance (Clement et al., 2018).

As often suggested in the literature, one potential pathway for smallholder farmers to improve their livelihood is to intensify production to increase their crop yields (Chartres & Noble, 2015). Depending on the context, this may imply improving crop nutrient supply (Droppelmann et al., 2016), pest, weed and disease control, improved varieties or crops and water management, consequently potentially increasing their farm income (Iddrisu et al., 2018) given favourable market conditions. Among the several intensification options widely discussed in the literature is the efficient application of mineral fertilizers (Yami & Van Asten, 2017), which is applied in low quantity across large parts of SSA (Pretty et al., 2011). Insurance may help farmers to increase the application of fertilizers, particularly under extreme weather conditions as seen from the results of this study. Without insurance, fertilizers might be too risky for resource-constrained farmers, though they add to annual expenses with no direct benefit in years with good weather. Several studies have also concluded that crop insurance increases the intensity of fertilizer applications among smallholder farmers, for example in Kenya (Bulte et al., 2020) and in Ghana (Sohngen & Wiredu, 2017).

## 5.4. Effects of basis risk weather index insurance

Despite many studies highlighting the potentials of WII, their subscription rates are still low with reasons ranging from low awareness and lack of knowledge of the insurance products to unprofitability for the insurance companies, and most importantly due to basis risk (Ankrah et al., 2021; Shirsath et al., 2019). Basis risk results from insurance contracts not being representative of the conditions experienced by farmers (Sibiko et al., 2018). Farmers are interested in insurance contracts with easy and understandable underlying calculations that can capture most of their climate-related losses, while insurance providers are interested in making profits. These conflicting interests are one of the main reasons why subscription rates remain extremely low. An incorrectly designed insurance contract will either lead to overestimation or underestimation of farmers' losses causing them to either not get paid when they record losses or get paid when they do not experience losses (Afriyie-Kraft et al., 2020; Ricome et al., 2017). Spatial basis risk arises when there are differences in geographical factors such as slope, altitude, latitude, longitude, and the distance between farms and weather stations (Afriyie-Kraft et al., 2020; Dalhaus et al., 2018). Using daily precipitation as a proxy for this means that we are examining how precipitation patterns vary across different geographical locations and how this variation might affect agricultural or climate-related outcomes. Temporal basis risk arises when WII does not accurately reflect the growth stage sensitive to specific weather, such as droughts (Dalhaus et al., 2018). Planting dates can show the variations in the growth stage of the crops and how incorrectly the WII contracts can capture the growth phase. Product basis risk refers to the discrepancy between the actual loss experienced by a farmer and the loss estimated or modelled by an agricultural insurance product (Muneepeerakul et al., 2017). Soil depth plays a critical role in determining a crop's resilience to weather conditions, especially droughts. Deeper soils generally have a higher water-holding capacity, which can sustain crops for longer during dry periods, while shallow soils, which characterise the soils in the study area (MoFA, 2017; Tetteh et al., 2016) are more susceptible to water stress. Using soil depth as a proxy, we acknowledge that two farms receiving the same precipitation might experience different levels of crop stress due to differences in soil depth.

The results here indicate that the effects of basis risk on WII effectiveness are greatest in the years when a crop failure is greatest, with errors due to either lower or higher soil depth compared with the actual soil depths of the farmers' sites. However, much of this may simply be an artefact of simulated assumptions about incomes and assets in good years, which vary considerably around the assumed reference conditions (Fig 14). Before shock occurs, farmers rarely notice any differences in their gross margins and farm assets as there are no need for indemnity payments. Basis risk can, therefore, be observed in years with extreme weather conditions (see Fig. 14 and 15), when there is a need for indemnity payment from the WII contracts. During these years, the indemnity payments cover farmers' losses, which helps to stabilise their gross margins. However, design errors in the insurance contracts can negatively affect farmers' economic conditions, as the selected index may sometimes fail to capture the shock. Notably, the results show that with higher precipitation, farm income and assets tend to decrease when compared to the normal precipitation in the study area. This is because precipitation is not the main limiting factor in the study area. The annual precipitation in the area exceeds 1000mm (with most of it occurring during the growing season). Nitrogen is the main limiting factor for maize yield in the study area and nitrogen loss through leaching increases with higher precipitation (Falconnier et al., 2020). The high impact of nitrogen leaching is, however, related to the shallow soil in the region, where water and nitrogen can be leached out very quickly (Kruseman, 2000; MoFA, 2017).

On the other hand, when looking at income and assets over the 5 years, many of the sources of basis risk had little impact on the overall probability of limiting the loss of assets. The notable exception was assumptions about soil depths, as farms that have much shallower soils than assumed by the index have an especially low probability of limiting losses of assets. This highlights the need to improve access and use of higher-resolution soil information data. However, though not significant, there is an effect of WII being less effective if farmers are planting earlier than the conditions assumed in the index (e.g., PD-14). Efforts have been made to offer ways of reducing the effects of basis risk on WII, thereby making these insurances more effective. Boucher et al. (2024) proposed an "audit clause of contract", where farmers can participate in detecting basis risk by reporting issues of inconsistencies. This can build trust in the insurance product and encourage farmers to purchase the contracts. In addition, several studies have highlighted measures that can help to reduce basis risk, including combining rainfall estimates from satellite and vegetation indices (Ntukamazina et al., 2017), utilizing high-resolution analysis tailored to the unique microclimates of farms, extensive rain gauge installations to capture triggers, and the establishment of community-based data sets with index thresholds (Afriyie-Kraft et al., 2020). In addition, efforts should be made to design these insurance contracts as close to farmers' environmental and economic conditions as possible, for instance, offering the insurance in areas where a particular highly covariate risk is the main source of loss (Barnett & Mahul, 2007). Finally, promising alternatives to supplying farmers with WII are to ensure their credit with lenders or to provide lines of credit which are contingent on experiencing a shock (Farrin & Miranda, 2015).

## 5.5. Study limitations

A key and overarching limitation in this thesis relates to the data quality of the household survey data, typical of many survey datasets (Fraval et al., 2019). We had a lot of variation in information ranging from yields to fertilizer rates to labour requirements for various cropping activities. A further main limitation is the assumption of constant costs. This approach was adopted for simplicity, as the focus was on weather uncertainty. Indeed, the weather data used were simulated data capturing a wide range of plausible weather, consistent with the current climate, and not actual observed historical data. Therefore, varying prices would have needed a complex approach based on current signals between crop prices as correlated with the weather. Such an analysis was largely unfeasible due to a lack of data and expertise. Ideally, adding yearly variation to input costs or at least conducting an uncertainty analysis would add robustness to the results of this study. Additionally, payment for household labour was not accounted for. In this case, the household expenditure and consumption were accounted for, but paying the household labour was not. The study did not account for the environmental costs associated with grazing of farm animals. This is because the farmers in the study area practice an extensive form of production and no reliable data to account for such costs is available. However, the study accounted for the associated labour costs for grazing. While these are serious limitations to the exact results of the thesis, they should not distract from the methodological advances in integrated risk assessment.

Another limitation of this study is that long-term crop rotation effects on e.g. soil organic carbon (SOC) on soil characteristics were not considered. The rotation effects were neglected because the simulations in this study were carried out over a relatively short-term period (5 years). In a future study, it would be interesting to see the long-term trajectory of SOC under different crop rotations and include such changes in the integrated model to optimise cropping systems, considering not only economic but also environmental aspects.

There were also various limitations associated with the crop model simulations regarding agronomic practice and impacts of extreme rainfall and excess wetness. Firstly, most local farmers do not apply pesticides, and the yield losses due to pests in this region are reported to be above 20% (Abudulai et al., 2012). While the crop model can simulate growth under different environmental conditions and management practices, it could not simulate waterlogging, lodging, pests, and diseases conditions, though empirical yield reduction was performed to bring yield levels close to reported levels. Second, wealthy farmers tend to use more improved seeds, such as hybrid maize. However, a single crop parameter set for each crop was used, meaning that the simulations do not capture the differences between improved and local seeds. Third, phosphorus deficiency is considered to be another major constraint to crop yield in Sub-Saharan Africa (Verde & Matusso, 2014), but among nutrient stress, only nitrogen stress was simulated with the crop model due to a lack of calibration data for considering phosphorus limitation. Despite these limitations, the crop model can simulate the main climatic risks in this region: drought from rainfall amount and dynamics, heat stress and the interaction of heat and drought, as well as effects of limited radiation and average daily temperatures. Advancing crop models in simulating diverse management options will help produce more realistic farm simulations, and thus, provide crucial information on designing insurance products. Furthermore, other factors apart from weather risk that can be associated with losses due to crop failure are not captured in the model and issues regarding the design of the weather index contract could lead to basis risk (Hill et al., 2019).

Furthermore, the insurance product was developed only for maize crops. The choice to develop and assess insurance solutions only for maize was based on several considerations. First and foremost, the maize response to nitrogen fertilizer in the region is highly variable, particularly with rainfall amount and water availability (Danso et al., 2018), making the investment in fertilizer very risky and potentially a case where economic returns of fertilizer use could justify the use of insurance. Other reasons included the interest of ACRE-Africa in the analysis of income of a maize insurance product as it is a food crop with the potential of securing food production in the region and increasing the spending power of the farmers in years with extreme weather conditions. This could increase the demand for insurance and then the insurance providers can introduce insurance for other crops. Additionally, the complexity of the study was limited to one crop. Finally, soybeans are commonly grown in the region under contracts, which precludes the use of an insurance product though likely with less favourable terms.

Finally, the model was simulated with a 5-year time series comprising an ensemble of 400 members for present-day climate. Ideally, a longer time series might include more extreme weather events, which could show more insurance payoffs. However, using these kinds of datasets would require combining different members, which may produce some artefacts where more extreme events can be included in some time series compared to others during the procedure of combining the members. Such extreme time series may not be physically plausible under current climate conditions. In the future, the HAPPI dataset comprising a 10-year time series of 800 members could be used (Mitchell et al., 2017).

# 6. General summary, recommendations, and contributions to knowledge

## 6.1. General summary

This study developed an integrated bio-economic model to simulate the impact of weather on farm management. The first focus was to compare the results of the integrated model with simulations from a household model (CLEM). The model offers a novel approach to risk assessment frameworks, which can help to understand risk management strategies and pathways to achieve sustainable intensification. Additionally, the model allows assessing trade-offs between crop management decisions and costs considering short-term effects, effects aftershocks and the long-term effects on incomes. By using a large ensemble climate forcing dataset, the model can assess the probabilities of outcomes. The conclusion from this study is that the integrated model provides more founded information for smallholder farmers under different weather conditions as the farm-level resource allocations are informed by environmental conditions, resource availability, and farmers' risk perceptions. Highlighting a current limitation of current optimisation approaches that do not consider weather variability, our results show different optimal crop allocation patterns depending on the weather case.

In addition, this study explored the effects of weather-index insurance contracts on farmers' long-term income and farm assets. The focus here was to assess the potential of insurance to stabilise farmers' income and increase farm assets in extreme weather conditions. The novelty of the study is to develop specific insurance contracts in collaboration with ACRE Africa, a well-known insurance service provider in SSA and evaluate these contracts along with the risk management option of replanting in the case of crop failure for effects on farm income and assets. From this study, it can be suggested that farmers are better off purchasing seed WII contracts that enable them to replant in extreme weather conditions and the event of crop failure as opposed to purchasing relatively expensive full insurance or having no insurance under these conditions. This is an interesting result because as widely mentioned in the literature, many smallholder farmers in SSA are faced with extreme poverty, with little chance of moving out of poverty traps. The results of this thesis suggest there may be potential for farmers to consider seed weather index-based insurance contracts, which would serve as a means of transferring their risks and increasing their ability to cope with climate change and other risks without excessive costs. However, looking at these contracts from a long-term perspective, they become expensive for the farmers as extreme weather conditions do not occur regularly. Therefore, more research to explore how to bundle insurance options with other interventions such as subsidies on inputs to ease the burden of the high cost of insurance on the farmers. In addition, insurance providers should focus first on introducing index insurance contracts for food crops (for example as presented in this thesis) as it has a high potential of securing food production in the region and increasing the spending power of the farmers in years with extreme weather conditions. This could increase the demand for insurance and then the insurance providers can introduce insurance for other crops.

## 6.2. Recommendations for future research

This study describes the integrated bio-economic assessment of climate risk and suitable risk management options for the case of smallholder farmers in Northern Ghana. Several areas where further research is needed were identified:

- Develop crop models to simulate more conditions leading to crop yield failure, such as waterlogging, pests, weed and disease damage. With crop modelling frameworks that can simulate diverse conditions, simulated crop yields would be more realistic as they would be closer to the farmers' actual yields and perhaps serve as an improved index for insurance products.
- Drive bio-economic model simulations with longer time series of a large ensemble climate dataset to capture more extreme events. Such simulations would be useful to capture the long-term effects of risk management options on farm resources. Effects of insurance for instance can take more than 5 years to show on farm income and assets, as well as on natural capital such as soil organic matter or biodiversity.
- Perform experiments that can detect farmers' preferences for risk management options under extreme weather conditions. Such experiments and simulation games can be helpful to understand why farmers would take up weather index insurance options as well as adopt other risk management strategies.
- Extend the work on exploring sources of basis risk to prioritise the data monitoring and information needed to design better indices.
- To apply the new integrated model framework together with various actors to support the design of insurance products to incentivise sustainability.

## 6.3. Contributions to knowledge

This thesis advanced current integrated modelling approaches for risk assessment contributing optimised knowledge on climate risk assessment and climate risk management in smallholder farming contexts. Specifically:

- The integrated bio-economic modelling framework provides a basis to assess the probability of different risk management strategies will provide short-term relief from the effects of shocks while supporting longer-term developments towards sustainability
- Less expensive seed coverage WII allows resource-constrained farmers to maintain incomes in years following a yield failure by allowing them to replant without excessive costs in good years
- Product basis risks such as those arising from incorrectly specifying the soil depth in the insurance design have a relatively larger impact compared to other forms of basis risks suggesting that higher resolution soil data is a priority to reduce basis risk for the conditions of smallholder farmers in Ghana.

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# 8. Appendix

Appendix A1- Updated framework of the integrated model to include WII-replanting scenarios.

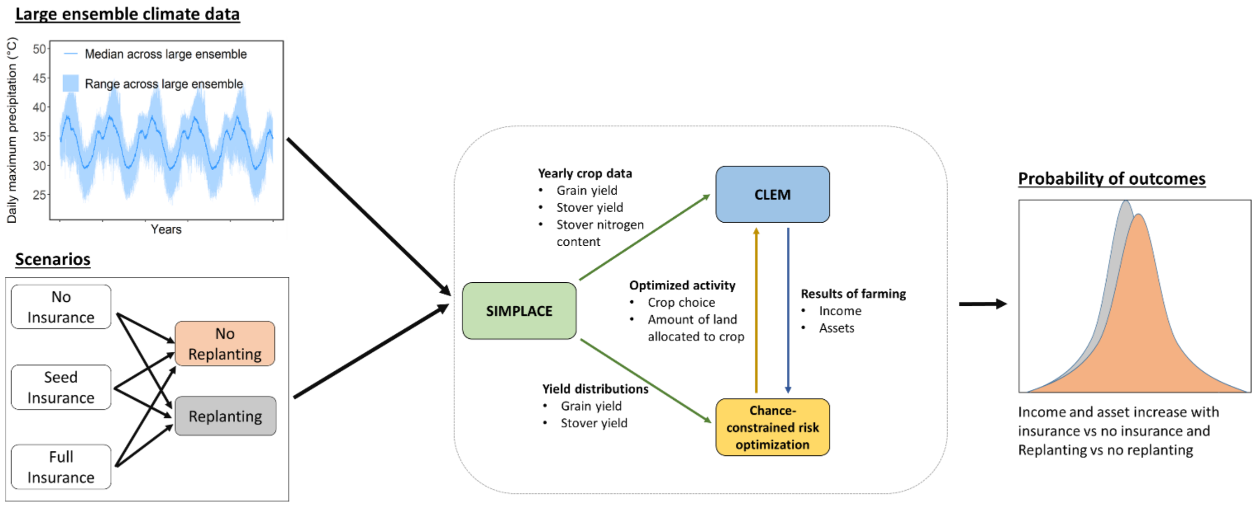

*Figure A 1. Updated framework of the integrated model to include WII-replanting scenarios. The large ensemble climate data is a generated global climate model data used to simulate all scenarios. The scenarios are a factorial combination of insurance contracts, including no insurance option with replanting and no replanting scenarios. The figure in the middle is the integrated model comprising CLEM, the crop model, and a farm optimisation model. The probability of outcomes depicts the results of the model, which are assessed in terms of probabilities.*

## Appendix A2- Updated flow charts of the integrated model for insurance-replanting scenarios.

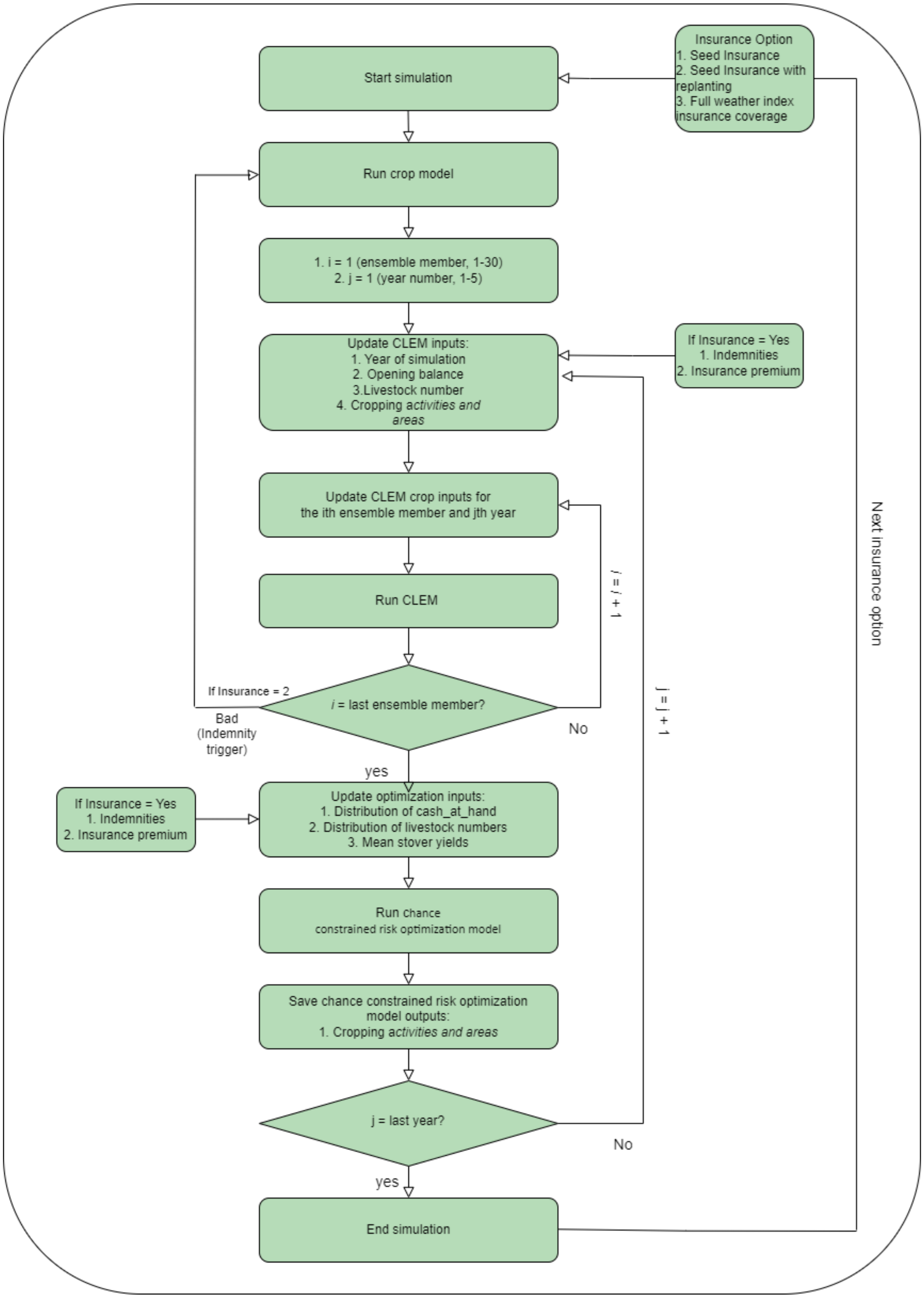

*Figure A 2. Updated flow chart of the integrated model*

## Appendix A3- Updated framework of the integrated model to include basis risk scenarios.

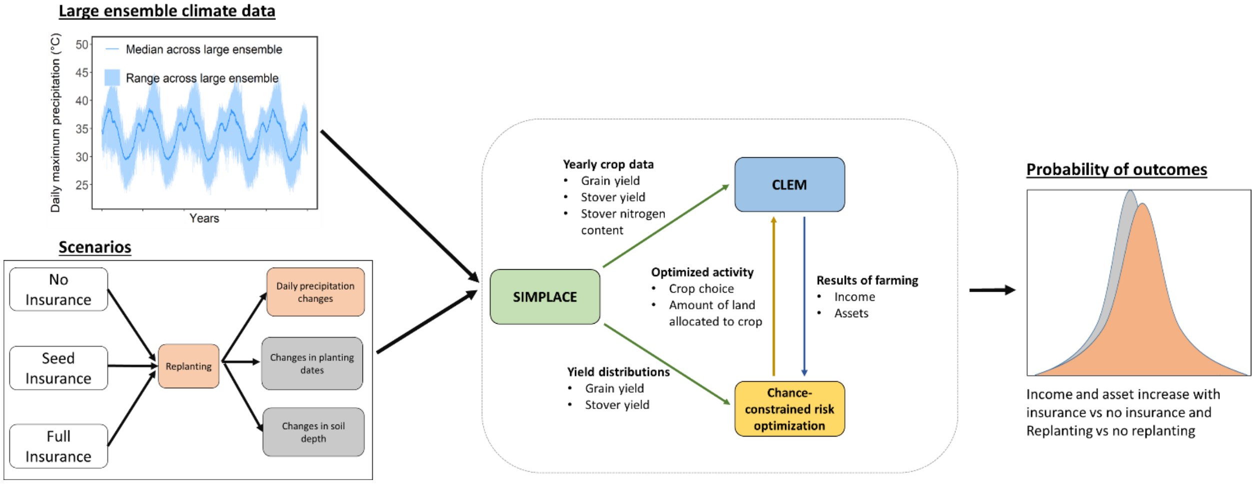

*Figure A 3. Updated framework of the integrated model to include basis risk scenarios. The large ensemble climate data is a generated global climate model data used to simulate all scenarios. The scenarios are a combination of insurance contracts, simulated under replanting assumption and yield data obtained from changes in daily precipitation, changing planting dates and changes in soil depth. The figure in the middle is the integrated model linking CLEM, with the crop model, and an annual farm optimisation model. The probability of outcomes depicts the results of the model, which are assessed in terms of probabilities.*

## *Appendix B- CLEM model assumptions.*

1. All farm types are modelled based on the farmers' current management practices as observed in the data.
2. All 100% of crop produce is sold, which is the main source of income in the model.
3. Other sources of fixed income are income from remittance, off-farm income, fixed income from livestock sales (i.e. poultry)
4. Ruminant mortality and fatality are not accounted for in the model.
5. The livestock are fed with residues for 7 months, which is typically the planting season in the study area and grassland for 5 months, which is typically the dry season period in the area. The grassland is infinite i.e. the quantities available are enough to feed all the animals for 5 months and there is no need to purchase other food sources during this period.
6. Farmers can obtain loans whenever their income is not enough to perform any activity. The size of the loan is limited based on data obtained for each farm type.
7. If the farmers' income falls to the negative and they obtain loans to carry out their production activities, there is an interest rate that must be paid.

8. Farmers sell livestock only if they do not have enough money to cover their household living expenses.
9. Labour activities are carried out by the household members and hired labour is used if the available labour is not enough. The costs of hiring labour are accounted for wage rate is obtained from the data.

Appendix C- Farm optimisation model assumptions.

The main assumptions adopted in parameterising the optimisation model include the following:

1. The crop yields are sold (100% sales as nutrition is not considered in the model. Only household feeding cost is included).
2. The biomass from crop production (obtained from the crop model), which is based on the land size and the crop type is fed to the ruminant livestock, in addition to grassland and additional feed supplements that may be bought based on the feed requirements of the animals and availability. The available residue quantity comes from the crop model and are updated each year.
3. These residues are fed to the livestock for 7 months and the animals graze on grasslands for the remaining 5 months of the year (during the rainy seasons- May to October). The feeds obtained from grassland are assumed to be sufficient for the animals and they have certain associated labour costs.
4. Each farming operation, including crop production and livestock production requires a certain amount of labour (total man days) and their costs (i.e. wage rate per day) were included as total labour cost.
5. Cash at hand is also included as part of the cash constraint. This was modelled in such a way that all income (excluding income from crop revenues as this should come at the end of the year) plus cash at hand and obtainable amount of loan must be greater than all expenditure.
6. If the farmers take loans, they must pay it back at the end of the year with interest. The interest rates and the maximum loan the farmers can take were obtained from the data
7. The total revenue on the farm includes revenue from crop production, off-farm income (fixed), income from remittances (fixed), income from poultry sales (this was obtained from the data, and the amount was modelled as a form of fixed income)
8. Livestock are held and not sold because farmers perceive them as a form of wealth preservation. The number of animals was, therefore, fixed, accounting for all associated costs to keep them.
9. The household food requirements were represented by their cost equivalents, taken from the household revenue

Appendix D- Optimisation model constraints.

In the following section, the production constraints as parameterised in the farm decision model are discussed in detail.

- *Crop production.*

1. The crop production activities in the region comprise maize (with varying degrees of fertilizer application intensity), rice, soybeans, upland rice, and groundnut, which are planted on the farmers' plots.

$$\sum_{c=1}^{C} X_{plot,c,typ} \leq land\_size_{plot,typ} \qquad (A4)$$

2. Equation (A4) shows that the sum of the cultivated crops per production plot must be less than or equal to the available land area per plot.

$$\sum_{i=1}^{mz} X_{plot.mz} * y_{mz,plot,typ} \geq \; total\_con_{typ} \qquad (A5)$$

3. Equation (A5) shows that maize yield must be at least equal or greater than the household consumption requirement.

- *Animal production.*

1. The animals are fed with the crop residues produced after harvesting the crops. To ensure that enough residues are produced or bought, a constraint was added stating that the total residue produced from own crop production and the possible amount that may be purchased is enough to feed the animals for 7 months and then the animals can graze on grasslands for the remaining 5 months of the year.

$$\sum_{i=1}^{plot,c,rc}(((X_{plot,c,typ} * f_{rc,c,typ}) * \; 0.583[3]) + \; \Sigma_{i=1}^{rc} \; rstd_{rc,typ}))) \geq \sum_{i=1}^{a}(foda_{a,fod} * hs_{a,typ} * 0.583) \qquad (A6)$$

2. Equation (A6) ensured that the total residue produced on the farm in 7 months plus the amount bought in kg is greater than or equal to the feed required by the total herd in the same period.

$$rsc_{typ} = \; \Sigma_{i=1}^{rc} rstd_{rc,typ} * res\_cost_{rc} \qquad (A7)$$

---

[3] Obtained by dividing 7 by 12 to represent 7 months of available forage in a year

3. Equations (A7) show the cost of residues bought.

- *Labour constraints.*

1. Labour is obtained from the household and hired labour. A labour constraint was introduced into the model to ensure that the crop production activity is restricted by the available household labour and a possible number of hired labour that the farmers can hire based on the cash available to them. All adults in the household can provide 30 man-days of labour per month, while young children mostly in their teens can provide 15 man-days of labour per month. Any additional labour required is provided by hired labour at the daily wage rate.
2. Equation (A8) shows that the adults in the households are available for 30 days, while young adults are available for 15 days in a month. The combination of these and hired labour sums up the total man-days of labour. Equation (A9) shows the cost of hired labour.

$$\Sigma_{i=1}^{mandays,plot,c}\left(lab_{mandays,plot,c,typ}\right) * \left(X_{plot,c,typ}\right) \leq \Sigma(\left(HH\_ad_{typ} * 30\right) + \left(HH\_y_{tpy} * 15\right)) + Hl_{typ} \qquad (A8)$$

$$Labcost_{typ} = Hl_{typ} * w_{day} \qquad (A9)$$

- *Cash constraints.*

1. Cash constraint was introduced to limit farmers' production activities based on the available cash and the possible amount of loan they can obtain at a particular time. The sum of the cash at hand, income from off-farm employment, income from poultry sales and the obtained loan must be equal to the total costs on the farm including the labour cost, and miscellaneous costs in equation (A10). Equation (A11) ensures that the farmers cannot obtain loans more than the amount they have already declared during the data collection process.

$$cash\_at\_hand_{typ} + off_{farm_{typ}} + loan_{typ} \geq Labcost_{typ} + total\_con_{typ} + tot\_exp_{typ} + all\_herd\_cost_{typ} + rental_{typ} + rsc_{typ} + tc_{typ} \qquad (A10)$$

$$loan_{typ} \leq \Sigma_{i=1}^{l}(l_{typ}) \qquad (A11)$$

- *Revenue*

1. The revenue included in the model is mainly from crop production as animals are not sold in the model. Other possible sources of revenue considered in the model are income from remittances and income from off-farm employment.
2. Equation (A12) shows that the revenues obtained from each plot should be equal to the yield per plot multiplied by the price per kg of the crop

$$cpr_{typ} = \Sigma_{i=1}^{plot,c} X_{plot,c,typ} * y_{c,plot,typ} * p_c \qquad \text{(A12)}$$

*Table S 1. Description of mathematical symbols used in the optimisation model.*

| **Symbol** | **Description** | **Units** |
|---|---|---|
| plot | The total area of cultivated plot | ha |
| land_size | Total available land area | ha |
| c | cultivated crop (the choice includes maize with low, maize with medium, maize with high fertilizer intensity, soybeans, rice, and groundnut | |
| mz | Maize crop | |
| total_con | Total consumption | |
| $f$ | available forage | |
| $rs_{bgt}$ | Total residue bought by the farmers | kg |
| $foda$ | feed requirements by the animals in kg | kg |
| $hs$ | The herd size of the farmer (including sheep, cattle, and goats) | |
| $rsc$ | Total cost of residue bought | GHS |
| res_cost | Price of residue per kg | GHS |
| $mandays$ | Total man-days of labour required | man-day |
| $HH\_ad$ | Adults in the household | |
| $HH\_y$ | Young adults in the household | |
| $Hl$ | Total hired labour | |
| $w_{day}$ | Wage rate per day | GHS |
| cash_at_hand | Cash at hand | GHS |

| | | |
|---|---|---|
| $off_{farm}$ | Income from off-farm employment | GHS |
| $l$ | Loan obtained by the farmers | GHS |
| $labcost$ | Total labour cost | GHS |
| $mc_c$ | Total miscellaneous cost | GHS |
| $ahd_c$ | Total herd production cost | GHS |
| $cpr$ | Revenue from crop production | GHS |
| $y$ | Yield per plot | GHS |
| $p$ | Price of crop per kg | GHS/kg |

Appendix E- Results from cropping activity scenarios.

*Table S 2. Scenario analysis of cropping activity under changing risk aversion coefficient*

| Weather | Farm type | Risk aversion coefficient | Land proportion allocated to crops | | | | | | Land area |
|---|---|---|---|---|---|---|---|---|---|
| | | | Maize low | Maize medium | Maize high | soybean | Upland rice | Groundnut | |
| Bad weather | LRE | 0 | 4.6% | 0.0% | 0.0% | 0.0% | 85.4% | 9.8% | 0.9ha |
| | | 0.0001 | 4.7% | 0.0% | 0.0% | 0.0% | 85.4% | 9.8% | 0.9ha |
| | | 0.001 | 4.7% | 0.0% | 0.0% | 0.0% | 75.8% | 19.6% | 0.9ha |
| | | 0.01 | 4.6% | 0.0% | 0.0% | 5.33% | 39.3% | 50.8% | 0.92ha |
| | | 0.1 | 17.4% | 5.8% | 1.7% | 38.8% | 21.3% | 15% | 0.92ha |
| | | 1 | 18.2% | 1.3% | 0.7% | 9.1% | 63.5% | 7.1% | 0.55ha |
| | MRE | 0 | 0.0% | 0.0% | 0.0% | 0.0% | 26.9% | 73.1% | 0.89ha |
| | | 0.0001 | 0.0% | 0.0% | 0.0% | 0.0% | 73.1% | 26.9% | 0.89ha |
| | | 0.001 | 0.0% | 0.0% | 0.0% | 0.0% | 80.1% | 19.9% | 0.91ha |
| | | 0.01 | 1.1% | 0.0% | 0.0% | 24% | 10.3% | 64.6% | 1ha |
| | | 0.1 | 21.6% | 0.0% | 0.0% | 39.9% | 4.1% | 39.9% | 0.73ha |
| | | 1 | 5% | 0.0% | 0.0% | 8.3% | 0.9% | 85.9% | 0.27ha |
| | HRE | 0 | 0.0% | 0.0% | 0.0% | 0.0% | 58.2% | 41.8% | 1.65ha |
| | | 0.0001 | 0.0% | 0.0% | 0.0% | 0.0% | 58.2% | 41.8% | 1.65ha |
| | | 0.001 | 0.0% | 0.0% | 0.0% | 0.0% | 40.6% | 59.4% | 1.92ha |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Good weather | | 0.01 | 9.1% | 0.0% | 0.0% | 55% | 10.2% | 25.7% | 2.28ha |
| | | 0.1 | 11.3% | 6.6% | 3.0% | 60.7% | 3.6% | 14.8% | 1.09ha |
| | | 1 | 5% | 2.9% | 1.3% | 31.1% | 2% | 57.5% | 0.08ha |
| | LRE | 0 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.92ha |
| | | 0.0001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.92ha |
| | | 0.001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.92ha |
| | | 0.01 | 0.0% | 0.0% | 0.0% | 0.0% | 100% | 0.0% | 0.92ha |
| | | 0.1 | 0.0% | 19.9% | 11.5% | 24.5% | 24.1% | 20.1% | 0.92ha |
| | | 1 | 23.8% | 17.7% | 13.2% | 30.1% | 6.7% | 8.5% | 0.61ha |
| | MRE | 0 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 3.36ha |
| | | 0.0001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 3.36ha |
| | | 0.001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 3.36ha |
| | | 0.01 | 0.0% | 0.0% | 0.0% | 10.9% | 52% | 3.1% | 3.11ha |
| | | 0.1 | 19.0% | 16.6% | 9.7% | 30.7% | 12.4% | 11.6% | 2ha |
| | | 1 | 23.2% | 17.6% | 13.1% | 30.7% | 6.8% | 8.6% | 0.58ha |
| | HRE | 0 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 5.13ha |
| | | 0.0001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 5.13ha |
| | | 0.001 | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 5.13ha |
| | | 0.01 | 9.8% | 1.1% | 0.0% | 21.7% | 38.3% | 29.2% | 4.38ha |
| | | 0.1 | 19.0% | 16.8% | 10.9% | 32.6% | 10.3% | 10.4% | 2.63ha |
| | | 1 | 19.1% | 17.1% | 12.7% | 35% | 7.4% | 8.8% | 0.47ha |

Appendix F- Survey questionnaire.

# 1 Farm area-

## a. area of the farm (estimated by the farmer)-

## b. no. of fields-

*Table S 3. Crop cultivation details – field/plot level for all crops (main, intercrop, relay crop)*

| Plots (no) | Total Area of the field (acre/ha) | **Current Season** | | **Previous season** | **Current season** | | **Previous season** | | | | **Current Season** | | | | % of produce kept for HH consumption (or in kg) | **Land preparation**<br>1 - ridge<br>2 - contour<br>3 - downslope<br>0 - zero<br>**Mechanization**<br>a) Tractor<br>b) Bullocks<br>c) Manual |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Land type**<br>**1- Upland**<br>**2- Lowland** | **Planting type**<br>**1- Sole**<br>**2- Intercrop** | **crop name** | **crop name** | Area proportion if intercrop (%) | Sowing date | Harvesting date | Production (Kg or bags) | Market price (GHS/Kg) | Production (kg or bags) | Market price (cedes /kg) | Use of residue<br>1- Burn 2- Incorp/Mulch,<br>3- Fuel<br>4- Grazing<br>5- Feeding<br>6- Selling<br>7- other | | | |
| [4]1 | [5] | | | [6]+[7] | [8]+[9] | | [10] | [11] | [12] | [13] | [14] | [15] | [16] | [17] | | |
| | | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | |

## 1.2. Crop Inputs (information needed for all fields/plots)

---

[4] [Plot] Plot number {plot_numbr}- All questions to be asked in a plot sequence order.

[5] [Plot] Declared area (ha) {declararea} and Plot delimitation (m2) {plt_delim}

[6] [Agricultural season] Previous season | If yes, crop type {yes_culcrp}

[7] [Agricultural season] Previous season | If yes, crop class {crop_class}

[8] [Agricultural season] Upcoming or current season | If yes, crop type {cult_crop}

[9] [Agricultural season] Upcoming or current season | If yes, crop class {crop_class2}

[10] [Sowing] Sowing date {sowin_date}

[11] [Harvest] Start date {start_date} and End data {end_date}

[12] [Agricultural season] Previous season | Grain production (in kg or bags) {output}

[13] [Post-Harvest] Marketing | Grain sales price (GHS/kg) {sale_price} – NB will be different from market price as this is the farmer declared price, equivalent to the farm gate price.

[14] [Agricultural season] Previous season | Residue production (in kg/bags) {output3}

[15] [Post-Harvest] Marketing | Residue sales price (GHS/bag) {sale_price2} – NB will be different from market price as this is the farmer declared price, equivalent to the farm gate price.

[16] [Agricultural season] Previous season | Fate of residue {fate_residue}

[17] [Agricultural season] Upcoming or current season | Intended use of residue {fate_residue2}

*Table S 4. Fertilizer and Manure (application, quantity, and price) for each field and crop from last year*

| [18]Fields/ plot | Crop Name | Seed<br>A-Own/local seed<br>B- Improved/high yielding seed<br>C- Hybrid | | | Herbicide spray (Chemical cost only)- no labour cost | | pesticide spray (Chemical cost only)- no labour cost | | Manure-Organic | | | | | [19]Urea cost @50 kg bag: ( ) | NPK fertilizers | | | Other fertilizer type Price () | Fertilizer application method<br>C-Micro dozing<br>B- Broadcasting<br>C- Through irrigation<br>D- Injection into soil |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | | CF-1 (N: __, P: __, K: __) cost @50 kg bag: ( ) | CF-2 (N: __, P: __, K: __) cost @50 kg bag: ( ) | CF-3 (N: __, P: __, K: __) cost @50 kg bag: ( ) | | |
| | | Variety/ cultivar | Quantity (Kg) | Price (/Kg) | No of times | Cost (/ spray) | No of times | Cost (/ spray) | Quantity (carts) | [20]Buy manure | | [21]Price if bought (cart) | [22]Application frequency | Quantity (Kg) | Quantity (Kg) | Quantity (Kg) | Quantity (Kg) | (Kg) | |
| 1 | [23] | | | | | | | | | Yes | No | | | | | | | | |
| | | | | | | | | | | Yes | No | | | | | | | | |
| 2 | | | | | | | | | | Yes | No | | | | | | | | |
| | | | | | | | | | | Yes | No | | | | | | | | |
| 3 | | | | | | | | | | Yes | No | | | | | | | | |
| | | | | | | | | | | Yes | No | | | | | | | | |
| 4 | | | | | | | | | | Yes | No | | | | | | | | |
| | | | | | | | | | | Yes | No | | | | | | | | |
| | | | | | | | | | | Yes | No | | | | | | | | |

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[18] Ensure that questions are asked in continuation of field level data obtained on section 1 above

[19] Obtain the cost price per 50kg of fertilizer.

[20] Ask if manures are bought or self-produced.

[21] Cart of manure- standard manure weight per cart

[22] Fertilizer application frequency- Daily, Weekly or Monthly

[23] If sole cropping, answer only one part of each field (plot). If Intercropping, answer both part

*Table S 5. Use of machinery and Bullock power for each field*

| | | | | Machinery and bullock hiring cost | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Ploughing | | | | | Hiring of Sprayer | |
| [24]Plot/ field | Tractor | | | Animal traction | | | | | |
| | No. of ploughing | C - Owned<br>B - Rent<br>C - Communal | [25]Cost (per use) | No. | C - Owned<br>B - Rent<br>C - Communal | Cost (per use) | Threshing cost | No of spray | Cost of hiring for each spray |
| 1 | | | | | | | | | |
| 2 | | | | | | | | | |
| 3 | | | | | | | | | |
| 4 | | | | | | | | | |
| 5 | | | | | | | | | |

---

[24] It is expected that land preparation activities are carried out by plot not by crop (i.e. intercropping)

[25] All associated costs, including labour cost.

*Table S 6. Labour use in cropping*

| [26]Field/plot | Crop Name | [27]Labour requirement (Days) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Land preparation | | Planting/Sowing | | Fertilizer application | | Manure application | | Weeding/ spraying | | Pesticide application | | Harvesting | | Post-Harvest/ Threshing | |
| | | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour | HH labour | Hired labour |
| 1 | | | | | | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | | | | | | |
| 3 | | | | | | | | | | | | | | | | | |
| 4 | | | | | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | | | | | |

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[26] Ensure that questions are asked in continuation of field level data obtained on section 1 above

[27] All labour requirements excluding land preparation labour requirements (e.g. ploughing, animal traction etc.)

## 2 - LABOUR DETAILS

*Table S 7. Off-farm labour for all household members*

| | Male (all in HH) | | | Female (all in HH) | | |
|---|---|---|---|---|---|---|
| | Period of the year | Days of engagement | Wage rate (GHS/day) | Period of the year | Days of engagement | Wage rate (GHS/day) |
| Off-farm work 1(Mention): | | | | | | |
| Off-farm work 2(Mention): | | | | | | |
| Off-farm work 3(Mention): | | | | | | |
| Off-farm work 4(Mention): | | | | | | |
| Off-farm work 5(Mention): | | | | | | |

*Table S 8. Peak labour shortage*

| | Very scarce | Scarce | Normal | Surplus | Very surplus |
|---|---|---|---|---|---|
| Ploughing | 1 | 2 | 3 | 4 | 5 |
| Sowing | 1 | 2 | 3 | 4 | 5 |
| Weeding | 1 | 2 | 3 | 4 | 5 |
| Spraying | 1 | 2 | 3 | 4 | 5 |
| Harvesting | 1 | 2 | 3 | 4 | 5 |
| Threshing | 1 | 2 | 3 | 4 | 5 |

*Table S 9. Hired labour daily wage rate*

| Period/seasons | Wage rate (GHS/day) |
|---|---|
| June to September (Rainy) | |
| October to January (Dry/Harmattan) | |
| February to May (Sunny) | |

# 3 - LIVESTOCK

*Table S 10. Details on livestock number and other information*

| Name of the livestock | Breed A- Local B- Improved | Sell milk (Yes/No) | Numbers | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Total Nos. | Milking (Y/N) | If Yes, No (kg/day) | Average age (Years/Months) | Average weight (Kg) | Cost (GHS/animal) | Sales price (GHS/animal) |
| **Cattle** | | | | | | | | | |
| **Sheep** | | | | | | | | | |
| **Goat** | | | | | | | | | |
| **Poultry** | | | | | | | | | |
| **Other animals** | | | | | | | | | |

3.3. Details of fodder fed to livestock for last year
How will you ask for these quantities? Possible? Alternatives?

*Table S 11. Grass(hay)*

| | | **If yes….** | | | |
|---|---|---|---|---|---|
| **Fodder** | **Do you feed this type of fodder (yes or no)?** | **For which months?** | **Source (residues from own fields or bought)** | **Quantity (Harvested/Bought) -If bought price/kg** | **Quantity fed to livestock (kg/day)** |
| Maize Stover | | | | | |
| Rice Straw | | | | | |
| Millets Stover | | | | | |
| Sorghum Stover | | | | | |
| Cowpea leaves | | | | | |
| Groundnut leaves | | | | | |
| Others (specify) | | | | | |

3.4. Do you graze your animals? (Yes/No)? If yes, answer section 3.3

*Table S 12. Animal grazing*

| Livestock | Period of grazing (i.e., rainy, dry or harmattan) | Time per day for herds | No. of labour required | Grazing distance (km) | Grazing cost (per total/day) |
|---|---|---|---|---|---|
| Sheep | | | | | |
| Cow | | | | | |
| Goat | | | | | |
| Others | | | | | |

3.5. Supplements fed to animals (if any)

*Table S 13. Inter-calving period and veterinary cost*

| **Livestock** | Inter-calving period (months) | Veterinary Costs (cedes/Year) |
|---|---|---|
| **Goats** | | |
| **Sheep** | | |
| **Cows** | | |
| **Other** | | |

*Table S 14. Labour use/herd for livestock*

| Period/seasons | **HH labour** | | **Hired Labour** | |
|---|---|---|---|---|
| | No. of days in a month | Hours/day | No. of days in a month | Hours/day |
| June to September | | | | |
| October to January | | | | |
| February to May | | | | |

## 4 – BUDGET DATA per farm for the previous year

*Table S 15. Previous year's budget*

| **Particulars** | **GHS** |
|---|---|
| General farm maintenance (like fencing, repairing and others) | |
| Electricity for farm or fuel costs | |
| Cash on hand at end of year | |
| Household's Living cost/month including children's fees etc. | |
| Any remittances (money from family working outside the village) | |
| Income from livestock (if any) | |
| Government cash transfers (if any) | |
| Other income | |

## 5 – Knowledge and Interest in SI options

*Table S 16. Have you heard about any of these practices?*

| | Never heard | Heard from other farmers | Heard from extension agents | Heard but practice occasionally | Heard and practised regularly |
|---|---|---|---|---|---|
| Fertilizer application and intensity | 1 | 2 | 3 | 4 | 5 |
| Use of improved short-duration varieties | 1 | 2 | 3 | 4 | 5 |
| Incorporation of residue after harvest | 1 | 2 | 3 | 4 | 5 |
| Intensive livestock production | 1 | 2 | 3 | 4 | 5 |
| Integration of small livestock | 1 | 2 | 3 | 4 | 5 |

*Table S 17. How much interest do you have in any of these practices?*

| | Not interested | Slightly interested | Neutral | Interested | Very interested |
|---|---|---|---|---|---|
| Fertilizer application and intensity | 1 | 2 | 3 | 4 | 5 |
| Use of short-duration varieties | 1 | 2 | 3 | 4 | 5 |
| Incorporation of residue after harvest | 1 | 2 | 3 | 4 | 5 |
| Intensive livestock production | 1 | 2 | 3 | 4 | 5 |
| Integration of small livestock | 1 | 2 | 3 | 4 | 5 |

## Appendix G- Publication lists

### Thesis related publications

(2024) Adelesi, O. O., Kim, Y., Schuler, J., Zander, P., Njoroge, M. M., Waithaka, L., Abdulai, A. L., MacCarthy, D. S., & Webber, H. The potential for index-based crop insurance to stabilize smallholder farmers' gross margins in Northern Ghana. Agricultural Systems, 221, 104130. https://doi.org/10.1016/j.agsy.2024.104130

(2023) Adelesi, O. O., Kim, Y., Webber, H., Zander, P., Schuler, J., Hosseini-Yekani, S.-A., MacCarthy, D. S., Abdulai, A. L., van der Wiel, K., Traore, P. C. S., & Adiku, S. G. K. Accounting for Weather Variability in Farm Management Resource Allocation in Northern Ghana: An Integrated Modeling Approach. Sustainability, 15(9), 7386. https://doi.org/10.3390/su15097386

### Other publications

(2024) Adelesi, O. O. Understanding farmer's diversity in non-timber forest products activities in Ogun State, Nigeria. Scientific African, 25(July), e02331. https://doi.org/10.1016/j.sciaf.2024.e02331

(2022) Adelesi, O. O., & Isiaka, O. Profitability analysis of smallholder aquaculture farms : the case of Lagos State, Nigeria. Journal of Agriculture and Rural Development in the Tropics and Subtropics, 123(1), 109–120. https://doi.org/https://doi.org/10.17170/kobra-202203085851

## Appendix H- Eidesstattliche Erklärung / Declaration under Oath

Ich erkläre an Eides statt, dass ich die Arbeit selbstständig und ohne fremde Hilfe verfasst, keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

I declare under penalty of perjury that this thesis is my work entirely and has been written without any help from other people. I used only the sources mentioned and included all the citations correctly both in words and content.

| | |
|---|---|
| ___________________________________ | ___________________________________ |
| Datum / Date | Unterschrift / Signature |

Ich erkläre, die wissenschaftliche Arbeit an keiner anderen wissenschaftlichen Einrichtung zur Erlangung eines akademischen Grades eingereicht zu haben.

I declare that the thesis has not been used previously at this or any other university to achieve an academic degree.

Datum / Date

Unterschrift / Signature

Erklärung über bestehende Vorstrafen und anhängige Ermittlungsverfahren / Declaration concerning the criminal record and pending Investigations

Hiermit erkläre ich dass ich weder vorbestraft bin noch dass gegen michErmittlungsverfahren anhängig sind.

I hereby declare that I have no criminal record and that no preliminary investigations are pending against me.

___________________________________ ___________________________________

Datum / Date Unterschrift / Signature

Appendix I- Curriculum vitae

# Opeyemi Adelesi

## EDUCATION

| | |
|---|---|
| Feb 2021 – | PhD Candidate– Martin-Luther University, Germany |
| Oct 2015 – Feb 2019 | MSc. Agricultural Economics – University of Hohenheim, Germany |
| Dec 2008 – Dec 2012 | BSc. Agricultural Economics – Obafemi Awolowo University, Nigeria |
| Dec 2005 – Oct 2007 | Diploma. Agricultural Technology – Lagos State Polytechnic, Nigeria |

## CONFERENCE PRESENTATIONS, SUMMER SCHOOLS AND TRAINING

| | |
|---|---|
| 2023 | TROPENTAG - Competing pathways for equitable food systems transformation: trade-offs and synergies (Conference) |
| 2023 | European Conference on Ecological Modelling (ECEM) - Ecological modelling for transformation (Conference) |
| 2022 | Modelling approaches for climate risk and climate change adaptations in the context of sustainable intensification in semi-arid West Africa. (Summer school in Senegal) |
| 2021 | International Conference of Agricultural Economists (ICAE) - Resilience and Food Security in North and West African Economies: Sustainable Farming Strategies and Household. (Conference) |
| 2021 | The Landscape Conference- Diversity for Sustainable and Resilient Agriculture. (Conference) |
| 2021 | Risk analysis and risk management in agriculture- Humboldt University, Berlin, and University of Göttingen (Course) |
| 2021 | Agent-based modelling in Agricultural and Resource Economics- IAMO Halle. (Course) |
| 2021 | Integrated land use modelling- University of BOKU, Wien. (Course) |
| 2021 | Economic modelling with the GAMS software- University of Gießen (Course) |

## RESEARCH POSITIONS

| | |
|---|---|
| May 2024 – | Research Associate – University of Applied Sciences, Rhein-Waal |
| May 2020 – April 2024 | Research Assistant – ZALF, Müncheberg |