Agricultural Systems 221 (2024) 104130

Contents lists available at ScienceDirect

Agricultural Systems

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

The potential for index-based crop insurance to stabilize smallholder farmers' gross margins in Northern Ghana

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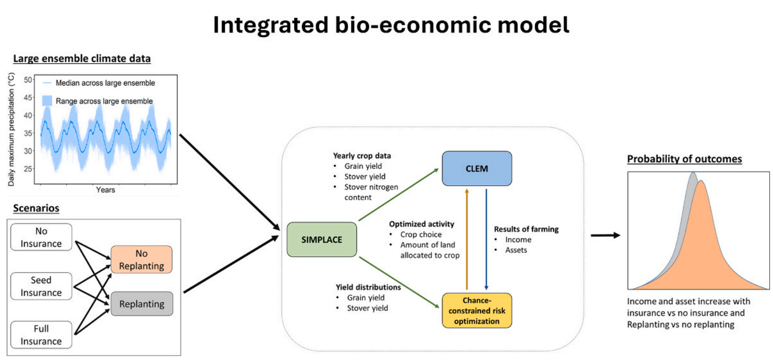
HIGHLIGHTS

- Integrated farm model explored weather index insurance.
- Full WII expensive, but more effective than seed WII.
- Costs must reduce for better outcomes.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Leonard Rusinamhodzi

Keywords:
Weather index-based insurance
Seed insurance
Bio-economic farm model
Integrated model
Weather risk
Northern Ghana

ABSTRACT

Context: Smallholder farmers in semi-arid West Africa face challenges such as weather variability, soil infertility, and inadequate market infrastructure, hindering their adoption of improved farming practices. Economic risks associated with uncertain weather, production and market conditions often result in measures such as selling 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 at the farm level. Proposed strategies include risk reduction through stress-resistant crop varieties and diversification, additional investments transfer options like crop insurance and contract farming. Despite experimentation with insurance products in sub-Saharan Africa, low adoption persists due to many factors including high premiums, imperfect indices, and cognitive factors.

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https://doi.org/10.1016/j.agsy.2024.104130
Received 12 January 2024; Received in revised form 28 June 2024; Accepted 2 September 2024
Available online 10 September 2024

Objective: The objective of this study is to assess the probability of two different index-based insurance products to stabilize smallholder farmers' income and limit asset losses in Northern Ghana using an integrated bio-economic modelling approach.
Method: We adapted an existing integrated bio-economic model comprising a process-based crop model, farm simulation model, and annual optimization model by including insurance contracts to assess their impacts on farmers' income and assets. We collaborated with an insurance service provider in sub–Saharan Africa to design and compare two weather index-based insurance contracts—one covering seeding costs and another addressing full input costs. Additionally, we considered the impact of management adaptations, such as replanting after crop establishment failure.
Results: The result from the study suggests that except for the most resource constrained, farmers would be better off purchasing seed insurance and replanting in the event of weather shocks, stabilizing their incomes and reducing the sale of their assets. These insurance options are less expensive than full weather index insurance for the resource-constrained farmers considering that extreme weather conditions do not occur regularly.
Significance: This study is significant for smallholder farmers in semi-arid West Africa, who are faced with economic and environmental challenges, challenging efforts to improve livelihoods. Focusing on Northern Ghana, the research assesses the viability of two index-based insurance products using an integrated bio-economic modelling approach. By presenting the probability of outcomes for income and farm assets, particularly through seed insurance incentivizing replanting after extreme weather shocks, the study offers a cost-effective solution for resource-constrained farmers. The results suggest the potential for weather-index insurance contracts to help smallholder farmers avoid bankruptcy or fall into poverty traps, especially after shock years.

1. Introduction

Smallholder farmers in semi-arid West Africa are faced with a range of challenges including low soil fertility, limited access to extension services (Fahad and Wang, 2018), insufficient market infrastructure (Briner and Finger, 2012; Hansen et al., 2019), and limited access to credit (Sanfo and Gérard, 2012). Experimental and modelling works show that various intensification techniques allow farmers to increase soil fertility, yields and thereby their average income (Danso et al., 2018; Ewert et al., 2015), but these benefits require smallholder farmers to invest in improved practices, as well as varieties or nutrient inputs (Gashu et al., 2019; Petersen and Snapp, 2015; Vanlauwe et al., 2014). At the same time, weather related shock, such as drought, flood, and their related risks of yield failure, which are projected to increase under climate change (Lesk et al., 2016; Trisos et al., 2022), make these investments particularly risky for smallholder farmers with little or low liquidity (Tang and Hailu, 2020; Yin et al., 2016). To overcome these challenges, while ensuring sustainability and profitability of farming systems, appropriate risk management strategies are needed.

Resource-constrained farming households in the region adopt several risk management strategies in the face of severe production and climate shocks, including liquidating assets, defaulting on loans, withdrawing children from school to work on farms, reducing household ration among others (Birthal et al., 2012; Hansen et al., 2019). Unfortunately, these strategies typically offer only temporary relief, as the affected households often struggle to return their livelihoods and farming activities to pre-shock levels (Boucher et al., 2022). This is primarily due to the erosion of vital productive assets like capital, livestock, and soil organic matter (Birthal et al., 2015; Frimpong et al., 2020; Hansen et al., 2019) and their risk attitudes (Arslan et al., 2017; Lehmann et al., 2013). Smallholder farmers tend to be more cautious in taking up innovations with higher costs or new production methods to minimize their losses in the event of a shock (Samuel et al., 2022). Although climate or production shocks affect farmers differently based on their resource endowments, it is widely held that many of these farmers fall into poverty traps as a result of the combined effects of asset loss and their inability to take prudent investment risks (Barrett and Brent, 2006; Boucher et al., 2022).

To support farmers to avoid poverty traps, there is a need for risk management approaches that can enable farmers to make sustainable investments on their farms. Several studies have evaluated different risk reduction strategies including 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 includes practices such as zero tillage (Pannell et al., 2014), mulching (Alary et al., 2016), and crop rotation (Rusinamhodzi et al., 2011) with the aim of minimizing soil disturbance and maintaining 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 good years (Danso et al., 2018; Faye et al., 2018), suggesting other risk management strategies, such as risk transfer (Di Marcantonio and Kayitakire, 2017; Sibiko et al., 2018), prudent risk taking and savings (Holden and Shiferaw, 2004), need to complement risk reduction.

Risk transfer measures such as index-based and indemnity-based crop insurance, and contract farming have been proposed to help farmers manage risks at the farm level (Ahdika et al., 2019; Leblois et al., 2014) and are known to enable investments and prudent risk taking (Aidoo et al., 2014; Bawa, 2019; Hansen et al., 2019; Laube et al., 2012; Traore et al., 2017). However, adoption is often low due to unprofitable terms, high basis risk and poor designs, 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). On the other hand, evidence suggests forms of social protection such as cash transfers may be an effective risk transfer mechanism enabling prudent risk taking (Ricome et al., 2017).

A wide range of insurance products have been tested across SSA including satellite-based, area-yield index insurance, and index-based livestock insurance among others (Ntukamazina et al., 2017). The most commonly known agricultural insurance in Ghana was introduced in 2011 under the Ghana Agricultural Insurance Pool (GAIP), 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. Consequently, most of the insurance products were discontinued by the insurance companies due to very low subscriptions (Afriyie-Kraft et al., 2020) and lack of government subsidies (Ankrah et al., 2021). Factors such as high premium rates, economic behaviour of farmers, and cognitive failure are among the reasons explaining low acceptance of index-based insurance in SSA (Arshad et al., 2016; Di Marcantonio and Kayitakire, 2017; Ntukamazina et al., 2017). While opinions about the usefulness and effectiveness of these insurance types are divided (Afshar et al., 2021; Binswanger-Mkhize, 2012; Clarke et al., 2013; Ricome et al., 2017), many studies expressed concern that insurance is not affordable for farmers without subsidies from the government (Arshad et al., 2016; Binswanger-Mkhize, 2012). More affordable insurance, such as index-based products, suffer from basis risk and lack of trust in the index (Collier et al., 2009; Conradt et al., 2015; Tadesse et al., 2015).

Recognizing the importance of insurance as safety nets in times of shocks, it is important to assess feasible insurance options considering farmers' incomes to inform the design of appropriate products. While several studies have explored the challenges, opportunities and the willingness to pay for weather index 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 assessed the effects of weather index insurance contracts on farmers' income considering uncertainty in future weather conditions. A key reason explaining the lack of such assessments to date may relate to the required methods of sampling much variability in weather and associated impacts on crop yields in farm system modelling (Adelesi et al., 2023).

Within this context, the objective of this study was to assess the performance of two different index-based insurance products and the probability that they would increase smallholder farmers' income and limit asset losses in Northern Ghana using an integrated bio-economic modelling approach. We collaborated with ACRE Africa (website: https://acreafrica.com/) to design and compare two different weather index-based insurance contracts: one less expensive product covering the germination phase and a second more comprehensive product covering the whole growth period, both compared with a no-insurance reference. We also explicitly tested the effect of replanting after an early failure of rains for each of the insurance cases.

2. Methodology

2.1. Study area

The study was carried out for the Northern Region which falls within the Guinea Savannah agro ecological zone of Ghana, with a land area of about 26,000km^2 (Northern Regional Coordinating Council, 2023). The region is characterized by a period of extremely low rainfall between October/November and April/May often referred to as dry season and a rainy season period usually from May to October (Braimoh and Vlek, 2004). It is characterized by a dry climate with annual rainfall that ranges between 750 mm and 1050 mm and an average annual temperature between 22.4 °C and 33.9 °C (Abdul-Razak and Kruse, 2017), which could get as high as 36 °C in March and April (Wiredu et al., 2010). Agriculture is the main occupation for the majority of the population as it employs about 70 % of the population (Amikuzuno and 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).

2.2. Farm survey data

Data for the parameterization of the model obtained in 2020 and 2022 in the study carried out by Adelesi et al. (2023). Data were obtained through questionnaires using the JotBi app, developed within the CGIAR CASCAID project (CGIAR, 2020). First, a household survey of 700 households was carried out across the Upper West Region, Upper East Region, and Northern Region during the 2020 agricultural cropping season. We filtered the dataset for the Northern Region households, reducing the data to 378 households located in the Tolon, Savelugu, and Mion districts. This was used to develop a farm typology, comprising of three farm types in the study area. Then a follow-up of in-depth survey of 15 households was carried out in 2022 on each of the farm types, totalling 45 households. The data obtained, which was used to parameterize the model include household socio-economic data, on-farm and off-farm income, farm assets and farm production data. Price data for year 2022[1] including crop and livestock prices were also obtained at the current market price and validated by experts at the Savanna Agricultural Research Institute in Tamale. Historical payoff average data (HPAD) from 1983 to 2022 used to calculate the insurance premium was obtained from ACRE Africa. The HPAD are location specific, and they indicate the percentage of historical claims at different growth phase of crops.

2.3. Model framework

To explore the effects of weather index-based insurance on farmers' income, we adapted an existing integrated bio-economic model that comprises a process-based crop model (SIMPLACE), a crop livestock enterprise model (CLEM) and an optimization model (Adelesi et al., 2023) as shown in Fig. 1. The optimization model simulates farm resource allocation in response to annual grain and biomass yield, accounting for the effects of farm management options on resources, recursively combining a bio-physical model to CLEM (details in Section 2.6.) and an annual optimization model.

2.4. Meteorological driving data

A large ensemble dataset containing 2000 years of current climate was generated using the EC-Earth global climate model data (Hazeleger et al., 2012). The ensemble consists of 400 members, with each member spanning 5 years for present-day climate conditions (the procedure for generating the large ensemble is provided in the Supplementary material). This large ensemble was used to capture as many extreme weather events as possible, consistent with current climate, which are often excluded with smaller datasets (including the historical weather record which is only one possible realization of current climate among many). The data were extracted for the grid point closest to the study site, Tamale (09° N and 00° W). Details on the large ensemble experimental set-up can be found in (Van Der Wiel et al., 2020).

2.5. SIMPLACE crop model

Crop grain, biomass yield and crop nitrogen content were simulated with the SIMPLACE crop modelling framework, which provided CLEM and the optimization model with a simulation of water, heat and nitrogen limited crop grain and biomass yield as described in (Adelesi et al., 2023). 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 dynamic (Addiscott and Whitmore, 1991). FAO-56 dual evapotranspiration method was used for evapotranspiration (Allen et al., 1998). To simulate the interaction between heat and drought, heat stress module (Gabaldón-Leal et al., 2016), was combined with canopy temperature module (Webber et al., 2016).

For the crop development and growth, 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 deficit both lead to reduced radiation use efficiency which in turn reduced 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

[1] We used the price data for 2022 because we parameterize the model with the survey data obtained in 2022

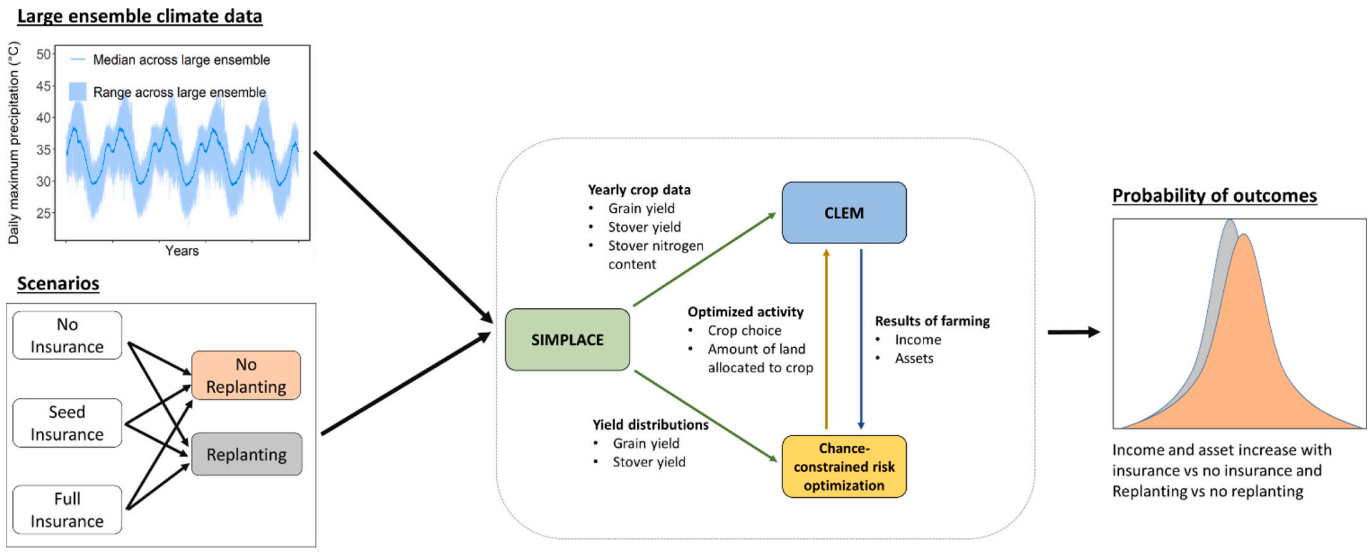

Fig. 1. A schematic depiction of the integrated model (Adapted from: (Adelesi et al., 2023 p. 5)). The large ensemble climate data is a generated global climate model data used to simulate all scenarios. The scenarios are a factorial combinations of insurance contracts, including no insurance option with replanting and no replanting scenarios. The figure in the middle is the integrated model comprising CLEM, the crop model, and a farm optimization model. The probability of outcomes depicts the results of the model, which are assessed in terms of probabilities.

multiplicative factors. These factors were introduced to account for yield-reducing influences that SIMPLACE was unable to capture. In addition to the crop model simulations for the grain and biomass yield, we also used the crop model to classify the 2020 data either as a good, bad or a normal meteorological year by simulating the crop model with stationary weather data.

2.6. Crop livestock enterprise model

The Crop livestock enterprise model (CLEM) is a comprehensive farm management tool that utilizes data from the biophysical crop-soil model to simulate on-farm resource flows. The model is developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO), and it integrates all farm resources (such as labour, capital, land, equipment) and management activities (including ploughing, weeding, fertilizer application, household consumption) to provide monthly assessments of factors like net income and food storage (for further details, refer to (Adelesi et al., 2023)). Insurance premium costs are considered as an input cost and potential indemnity payments are included in the gross margin of the farms when the index is triggered (see Section 2.8).

2.7. Optimization model

The farm optimization model, originally developed in Adelesi et al. (2023) was modified to include the insurance contracts. The model is a non-linear mathematical programming model parameterized based on the farm household production activities in the region. The model includes risk as a result of fluctuations in yield (due to weather variability) of the contributing margin of activities, maximizing the certainty equivalence of the farmer's gross margin (Eq. 1) and, assuming that farmers have certainty about the resources at the beginning of the year (Eq. 2) but uncertain about others (Eq. 3), which are accounted for with a given probability (Maher and Williams, 1999). However, other components of gross margin, i.e., product prices and production costs are assumed to be fixed.

Indemnities are treated as variable income that is added to the gross margin in the event of a payoff. The model accounts for insurance premiums as fixed costs (except in the case of no insurance), which are included in the gross margins (Eq. 1). The premiums are deducted from the gross margins in scenarios with insurance, as shown in Eq. 4. To account for the effects of insurance on farmers' risk attitude, the indemnities were included in the risk premium as in Eq. 5. Based on Moss (2010) and Conradt et al. (2015), we used absolute Arrow-Pratt risk aversion coefficient to calculate the risk premium (Eq. 5).

$$Max : \mathrm{CE} = \mathrm{E(GM)} - \mathrm{RP} \tag{1}$$

where.

CE = Certainty equivalence of farmer's gross margin.
E (GM) = Expected gross margin.
RP = Farmer's risk premium.
subject to:

$$\sum_{j=1}^{j} \mathrm{aijxj} \leq \mathrm{bi}\ \mathrm{i} = 1, \dots, \mathrm{n} \tag{2}$$

$$\mathrm{Prob}\left[\sum_{j=1}^{J} a_{mj}x_j \leq b_m\right] \geq \beta\ m = 1, \dots, M \tag{3}$$

$$\mathrm{E(GM)} = \sum_{j=1}^{J} \mathrm{E}\left(\mathrm{cm_j} + \mathrm{ind_j}\right)\mathrm{x_j} + \mathrm{R} - \mathrm{PR} \tag{4}$$

where.

$\mathrm{ind_j}$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.

$$\mathrm{RP} = 0.5\rho \sum_{i=1}^{j} \Sigma_{i=1}^{j}\ \mathrm{v}\left(\mathrm{cm_i} + \mathrm{ind_j}, \mathrm{cm_j} + \mathrm{ind_j}\right)\mathrm{x_i x_j} \tag{5}$$

where.

RP is the risk premium.
ρ is the farmer's absolute risk aversion coefficient.
$\mathrm{v}\left(\mathrm{cm_i} + \mathrm{ind_j}, \mathrm{cm_j} + \mathrm{ind_j}\right)$ is the variance covariance matrix of the ith and the jth activity's contribution margin and the indemnities.

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 for the calculations of risk premium in Eq. 5 above.

2.8. Weather index insurance options

Weather index-based insurance contracts were developed for maize as it is one of the most important crops in Northern Ghana (Antwi-Agyei et al., 2018), with a larger share of cultivated land areas of the farmers' land (Ankrah et al., 2021; Danso et al., 2018; Lucas et al., 2019). The contracts were developed in collaboration with ACRE Africa, an insurance service provider in sub-Saharan Africa. 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 on 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 is considered as the major risk 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."

The product covers a period of 120 days with a specific planting date and comprising of 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, we observed the planting dates from our survey, which averaged to June 12th. We further discussed the dates with experts that 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), that states that June is usually regarded as the normal planting date in Northern Ghana, while May and July are early and late planting dates in the region. Furthermore, we compared the affordability and efficiency of two insurance products, namely seed insurance, and the full weather index insurance cover, which comprise of 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 premium for the insurance. The full weather index insurance 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.

2.8.1. The weather index

Both weather index products utilize daily rainfall observations from the Tamale (09° N and 00° W) grid point to assess risk during the cropping season. Here we consider the extracted data from EC- Earth global climate model data for year 2011 to 2015 to calculate the weather index. We used this data because they are the same data that we used to run the integrated model, and this would ensure uniformity. We however, compared the data with the TAMSAT dataset for the same years, which gave similar results. Triggers are set based on rainfall deficits and excesses per growth phase of the historical rainfall events. For the index, we did not consider temperature and evapotranspiration because we aim to develop insurance contracts that are as close to the study area as possible. We considered only rainfall deficits and excesses because fluctuations in rainfall is considered as the major risk faced by the farmers in the region (Haile, 2005). In addition, standardized Precipitation Evapotranspiration Index (SPEI) requires additional inputs to compute potential evapotranspiration, which may increase uncertainty (Hoffmann et al., 2020), especially in areas where good-quality and high-resolution climate data are missing, such as our study site. 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 very 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 5th percentile of the average daily observed rainfall data as represented by Eq. 5 and during the maturity phase where excessive rainfall is the main peril, the trigger was determined by 95th of the average daily observed rainfall data, as shown in Eq. 6.

$$T_{phase} = P0.05\left(\mu\left(\Sigma_{phase}^{d}\right)\right) \tag{5}$$

where

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

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

$$T_{phase} = P0.95\left(\mu\left(\Sigma_{phase}^{d}\right)\right) \tag{6}$$

where

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

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

2.8.2. Indemnities

Indemnities are computed individually for each growth phase. For the GC phase, the cumulative rainfall over 14-day intervals is 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). If at any point during the 14-day period, the total rainfall received is less than or equal to the trigger value, a loss event is deemed to have occurred, and indemnity payouts are accumulated (Berg et al., 2009). 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 is calculated. During any period of 21 days, if the total rainfall received is less than or equal to the trigger value 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 of 25 % each as shown in Table 1. To determine the loss compensation per phase, we estimated the number of intervals for each growth phase based on the daily rainfall data as shown in Eq. 7.

$$N_{interval} = \left(N_{Dphase} - R_{cumP}\right) + 1 \tag{7}$$

where

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

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

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

Table 1
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 Sowing costs
Full insurance cover	Germination	25 %	21	14	8	3.1 %	Seed costs Sowing costs
	Vegetative	25 %	45	21	25	1 %	Fertilizer costs 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 was determined by dividing the maximum loss payable in each phase by the total number of intervals. We then obtained the number of intervals where the trigger is set for each phase (in section 2.6.3). The number of intervals with the trigger set were then multiplied by the loss compensation per interval to obtain the percent of input costs to be paid per phase. The seeding costs (Table 1) used in the germination phase include the costs of seeds and sowing associated costs such as labour were obtained from the survey. These are similar to other input costs used in Table 1 and we used these costs to ensure that the insurance contracts consider the farmers' current management practices as much as possible.

The loss compensation per interval shown in Table 1 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 depend on the growth phase of the crop as shown in Table 1. 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, we averaged all the indemnities in the germination phase that were greater than 0 i.e., cases were there were payouts.

2.8.3. *Insurance premium*

The insurance premium for the different types of contracts used for this study were calculated 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 payoffs 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 weather data used for the historical payoffs were obtained from TAMSAT (website: https://gws-access.jasmin.ac.uk/public/tamsat/) for Northern part of Ghana region. The region was divided to the TAMSAT grid points of 4 km by 4 km resolution. This historical data ensures that the premiums are farm-specific, which reduces adverse selection problems (Bucheli et al., 2021). Further, we estimated the capital loading; an extra cost added into an insurance policy to cover for unanticipated losses a key component 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 of 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 Eq. 8.

$$\mathrm{CL} = \mathrm{A_{cb}} \times (\mathrm{P0.95} - \mathrm{A_l}) \tag{8}$$

where

CL = Capital loading

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

P0.95 = 95th percentile

$\mathrm{A_l}$ = 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 the agriculture insurance contract and profit of the insured. The pure premium was calculated as the sum of average losses and the capital loadings (Benjamin, 1986) in Eq. 9. The gross premium was then calculated by adding the pure premium, the commissions, and expenses as shown in Eq. 10.

$$Pr = CL + \text{Average losses} \tag{9}$$

where.
Pr = Pure premium (pure risk)

$$\mathrm{GP} = Pr + \Sigma(C_m) \tag{10}$$

where.
GP = Gross premium.
$\mathrm{C_m}$ = Commissions.

With the additional 20 % added for commission, this means we have made 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.

2.9. *Farm typologies*

The initial conditions for the different farm types described and simulated in Adelesi et al. (2023). These farm types include low, medium, and high resource endowed farms (LRE, MRE and HRE respectively). These farms are categorized based on their resource endowments; such resource include land and herd size, capital assets and household size. LRE farms are characterized by small household size and an average land size of 0.9 ha, with low on-farm and off-farm income. MRE farms are relatively average household sized farms, with farm size of about 4 ha, they have relatively high off-farm income and average on-farm income. HRE farms are relatively large farms with about 6.9 ha land size, they have relatively higher on-farm incomes.

2.10. *Simulation set-up*

Simulations were conducted for the three insurance options: no insurance, seed insurance and full insurance in a factorial combination with replanting options as summarized in Table 2. These options were evaluated for each farm type. Crop model simulations were conducted for all the crops cultivated by the farmers namely: soybeans, groundnut,

Table 2
Summary of simulation experiment options.

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		

rice, and maize. These were obtained from the data obtained in the study area. Maize crops were simulated with varying degrees of fertilizer application rates from low to high regarded as maize-low, maize-medium, and maize-high with 17.5 kg N/ha, 49.4 kg N/ha and 114 kg N/ha respectively (Adelesi et al., 2023).

2.11. Replanting and no-replanting

Replanting after crop failure due to low or excessive rainfall is an effective measure in offsetting yield losses (Sisterson and 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, we included options for replanting during an extreme case of crop failure. We simulated the crop model for an alternative planting date (i.e., July 10- one month after 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 extreme case that leads to crop failure, the indemnity payment indicating the losses must exceed a 75th percentile threshold of (i.e., highest 25 %) of the indemnity payments. Replanting cost was also added for replanting scenarios, and these included the cost of seeds and sowing associated costs i.e., cost of seed, cost of herbicides and fertilizers. In case of total yield loss and for the no replanting scenarios, we assumed that the corresponding yields for these extreme cases were 0. We did this to avoid the disparities and inaccuracies of accounting for yield losses during crop yield failure.

2.12. The integrated model simulation assessment

To incorporate insurance contracts and the possibility of replanting in the event of yield failure, simulations were also 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. The resulting crop grain and biomass yield data were stored in a database to be used by the CLEM and optimization models. Further, we calculated the indemnities for all possible weather scenarios and determined the premiums for maize crop. CLEM simulations were executed for each member of the weather data ensemble, generating 400 independent outputs. The optimization model simulated annual crop and land allocation, which were then updated in CLEM for the following year (year 2), as illustrated in Supplementary material (Fig. A1). Simulations were repeated for each farm type, insurance option and replanting scenarios as shown in Table 2. We analyse results for one specific 5-year time series that has a shock year to understand the model reactions across different types of years and in case of weather shocks. After this, we present the probabilities of higher income and increased farm assets after 5 years for all the scenarios.

3. Results

3.1. Household, agronomic and economic characteristics of the study area

Household size, input costs and farm endowments are part of the differentiating variables among the farm types in the study area. This is shown in Table 3, where HRE farms with an average of about nine people in the household are relatively larger than other farm types. This means that HRE farms would spend relatively more on consumption per annum compared to other farm types. On the other hand, a large household size could mean that more people in the household are available for household labour. Farmers in the study area apply a range of about 18 kg N/ha to about 144 kg N/ha for maize crop despite that the crop contributes a negative gross margin. This is expected as maize is mostly cultivated for household consumption in the study area (De Jager et al., 2018; Nti, 2008). In addition, the seeding costs for maize is relatively lower compared to the other crops and it ranges from as low as 19 GHS/ha to about 57 GHS/ha.

3.2. Crop yield

The simulated maize yield with the different fertilizer intensity is presented in Fig. 2. As expected, maize yield increased with increasing nitrogen fertilizer rates, an average yield of 3000 kg 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. Replanting occurred only in about 4 % of the weather realizations. Results from classifying the 2020 weather shows 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.

3.3. The insurance contracts

The premium and the average indemnities for the insurance contract are presented in Table 4 and Fig. 3. Seed insurance is relatively inexpensive as farmers are required to pay less than 30 GHS[3] ha^{-1}, while full insurance cost about 113 GHS ha^{-1}. The indemnity payment for the seed insurance is 161 GHS ha^{-1} as payments are not partial[4]but full regardless of the degree of crop failure. On the other hand, full insurance cover can in some cases pay extremely low indemnities and in other cases pay as high as 600 GHS ha^{-1} depending on the degree of indemnities. In addition, results from Table 5 shows that more indemnities are recorded in the vegetative growth phase in the case of full insurance, and this cumulates to an average of about 100 GHS ha $^{-1}$. Details about the results of the input parameters such as the triggers at each phase and the commissions are shown in Table S1 in the Supplementary material.

3.4. 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. We illustrate the effects of insurance options and replanting scenarios on farmers' income and assets as presented in Figs. 3 and 4. The annual farm income and assets represented in Figs. 3 and 4 are the annual gross margins and farm assets (livestock and cash at hand) obtained from

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

[3] GHS refers to Ghanaian Cedis, which as of August 23, 2023, exchanged for 11.24 GHS for 1 US Dollar

[4] This is why we did not present the full indemnity payment for seed insurance in Figure 3 since we used only average indemnity payments

Table 3
Descriptive statistics of farm type and economic analysis of current production.

Household data		Unit	LRE[a]	MRE[b]	HRE[c]			
Household size			2	3	9			
Household living cost		GHS/year	120	735	981			
Off-farm income [d]		GHS/year	1367	2209	2339			
Farm operating cost [e]		GHS/year	410	626	1048			
Cash at hand		GHS/year	126	1331	2393			
Average loan amount		GHS/year	47	1906	2536			
Loan rate		% / month	8	8	8			
Total land area		ha	0.9	4.0	6.9			
Herd size			14	18	20			
Poultry number			14	19	18			
Agronomic data		**Unit**						
			Maize (LFI)[f]	Maize (MFI)[g]	Maize (HFI)[h]	Soybean	Upland rice	Groundnut
Nitrogen fertilizer rate		kg N/ha	17.5	49.4	114.3	17.4	49.2	3.6
		SD[i]	6.3	24.5	19.4	14.2	45.8	7.4
Average yield		Kg/ha	660.6	2162.2	3294.7	1600.9	4229.0	3037.3
		SD	388.9	1656.1	1496.3	1547.8	3184.5	2533.4
Economic data		**Unit**						
Input cost	Tillage	GHS/ha	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		GHS / ha	1530.5	4654.7	7126.5	2696.3	4011.2	3570.4
Average yield		kg / ha	660.6	2162.2	3294.7	1600.9	4229.0	3037.3
Crop price		GHS/kg	1.7	1.7	1.7	1.8	1.5	1.7
Total revenue		GHS / ha	1101.0	3603.6	5491.2	2935.0	6343.5	5062.2
Gross contribution (GHS / ha)		GHS / ha	676.7	2051.9	2489.3	2279.6	4941.1	4404.7
Contribution margin		GHS / ha	−429.5	−1051.1	−1635.3	238.7	2332.4	1491.9

[a] Low resource endowed farm.
[b] Medium resource endowed farm.
[c] High resource endowed farm.
[d] All non-farm income including remittance, income from livestock sales and off-farm employment.
[e] All farm cost including farm maintenance, energy cost, machinery rental cost and livestock feeding cost.
[f] Low fertilizer intensity.
[g] Medium fertilizer intensity.
[h] High fertilizer intensity.
[i] Standard deviation.

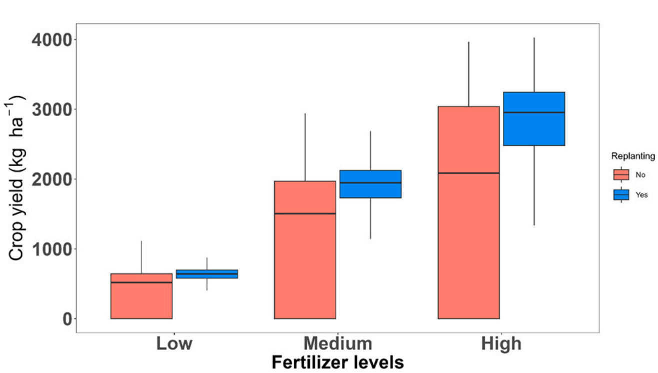

Fig. 2. Distribution of maize grain yield across fertilizer levels and with and without replanting. The red boxplots represent crop yield from no-replanting scenarios and the blue represents the yield from replanting scenarios. The horizontal line in the middle of the boxplot shows the median and the upper and lower lines show the interquartile rage. The whiskers span from the edge of the box to the furthest data point within 1.5 times the interquartile range below it. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

simulating the optimized cropping pattern with the farm management activities in the simulation model (CLEM). In Fig. 3A, for both MRE and HRE farms, with relatively larger farm size 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 size, the effects of insurance are not big enough because they only purchase small size insurance contracts. As expected, in year 1 and 2 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 in Fig. 3B, 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 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 time 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 lack of insurance, leading to inability of the farmer to either continue farming or meeting the household needs. This can be observed with the MRE and HRE farms without insurance options recording very high losses during the shock years.

Fig. 4 also shows that in the case of shocks insurance options preserves farmers' assets better than no insurance options. This is because

Table 4
Premium and average indemnity payments for weather-index insurance contracts.

Crop	Insurance cover	Growth phase	Premium (GHS/ha)	indemnity payments (GHS/ha)		
				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 over all weather ensemble and years.
[2] Average non-zero indemnity payments over all weather ensemble and years.
[3] Maximum indemnity payments over all weather ensemble and years.

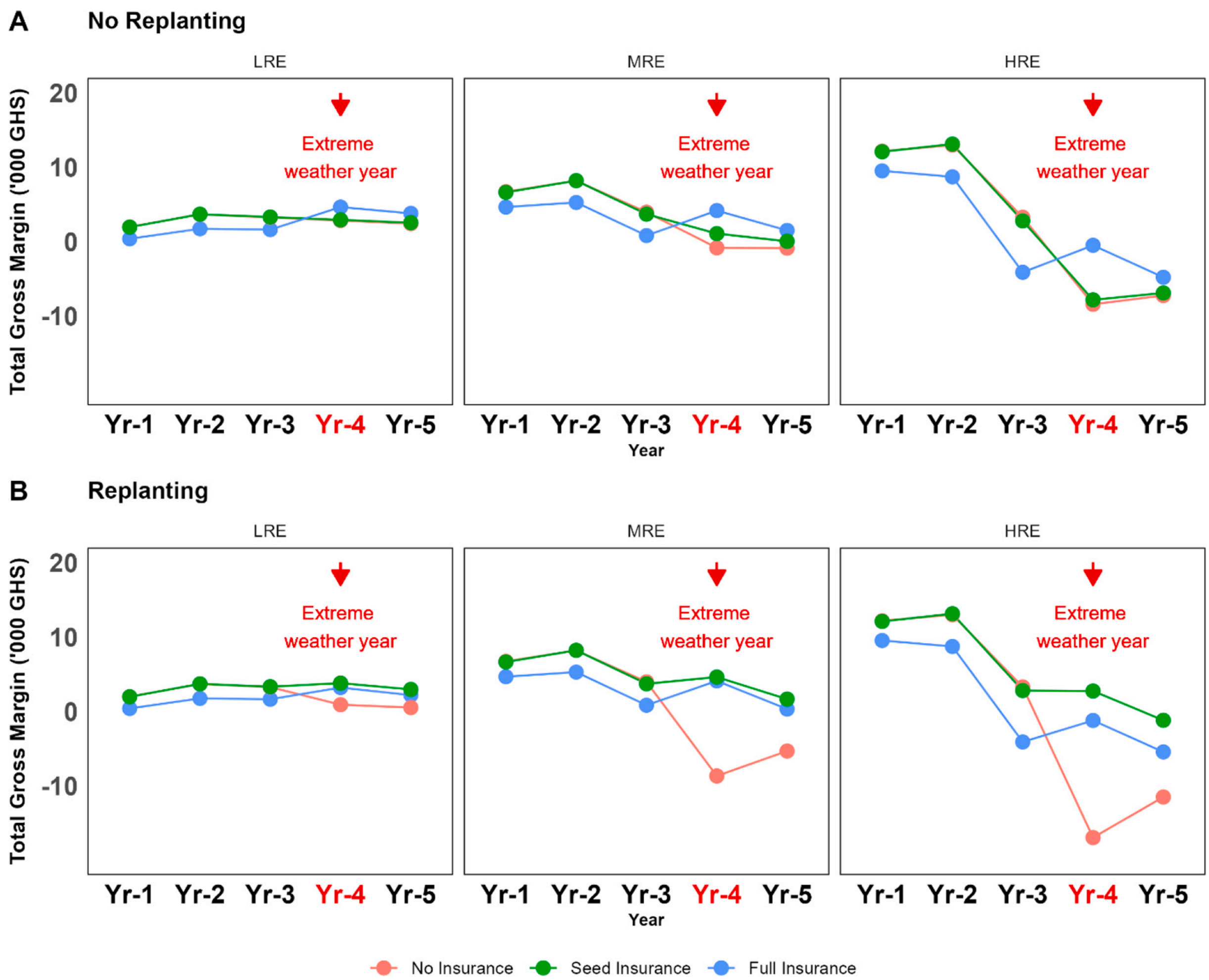

Fig. 3. Time-series of gross margins under extreme weather condition. A- represents the no-replanting scenarios, while B- represents the replanting scenarios. The left plots are for the low resource endowed farms (LRE), the middle plots are for the medium resource endowed farms (MRE) and the right plots 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. The orange points on the plots shows cases where farmers could not replant. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the farmers are likely to receive compensation from insurance when shock occurs and they can use such compensation to either meet household needs (Fig. 4A- no replanting) or replant for more yield (Fig. 4B), thereby reducing the need for them to sell their assets. However, as shown in Fig. 4, full insurance options are expensive when there are no shocks.

3.5. *Insurance and land allocation under shock*

To explore the effects of the different insurance options on optimal farmer decision making and resulting allocation to different cropping activities, as in Section 3.3, we used the same 5-year time series. 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 Fig. 5. Results from Fig. 5A shows that following a normal weather year (for maize productivity), relatively smaller farms (LRE and

Table 5
Average Index, indemnity count[1] and Indemnity payments per year and growth phase.

Year	Insurance	Growth_phase	Index (mm)	Indemnity (GHS/ha)	Index Count
1	Full Insurance	Germination	13.4	37.3	4
2	Full Insurance	Germination	10.9	32.3	3
3	Full Insurance	Germination	14.2	35.5	4
4	Full Insurance	Germination	12.7	34.6	4
5	Full Insurance	Germination	11.5	37	4
1	Full Insurance	Vegetative	18.1	115.5	5
2	Full Insurance	Vegetative	15.7	88.8	4
3	Full Insurance	Vegetative	22	119.5	6
4	Full Insurance	Vegetative	21.6	81.2	4
5	Full Insurance	Vegetative	18.9	100.7	5
1	Full Insurance	Flowering	30.1	14.1	2
2	Full Insurance	Flowering	42.7	20.5	4
3	Full Insurance	Flowering	37	16.7	3
4	Full Insurance	Flowering	58.6	12.6	2
5	Full Insurance	Flowering	43.2	20.9	4

[1] The indemnity count is the number of times index is triggered in each weather timeseries.

MRE farms) allocate about 25 % of their land to maize with low fertilizer intensity in all the insurance options. However, in a bad weather (Fig. 5B), 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, under normal weather conditions (Fig. 5A), they cultivate 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 climate shock, they increase 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 stabilizing farmers' income in shock years, it is interesting to also know that these shock years do not occur regularly.

3.6. Probabilistic effects of insurance on income

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 Fig. 6. We compared the income at the second year (year 2) of simulation to the last year of simulation (year 5). We excluded the first year of simulation from the probability calculation to remove the effects of optimization on farm income. Result from Fig. 6 shows that on average, considering all the possible weather conditions, seed and full insurance options does not significantly increase farmers average income compared to a case of no insurance. This is shown in Fig. 6, where the farm households have 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 of the replanting scenario in Fig. 6, where the farm households have about 50 % probability of increasing their farm income after 5 years in all the 3 insurance options.

3.7. Insurance and long-term farm assets

Herd size plays an important role in determining how financially stable a smallholder farmer is because they are known to keep livestock as a form of liquid asset (Breckner, 1958; Siegmund-Schultze et al., 2007). To assess the effects of insurance on farm assets, we combined the monetary value of the available livestock with cash at hand, and tested the probability that these assets will increase after 5 years in all the different scenarios as shown in Fig. 7. From the result, on average farm assets for the all the farms are likely to decrease after 5 years, and the outcomes are similar for the different insurance options and replanting scenarios. This is shown in Fig. 7 (both with no replanting and replanting scenarios) with about 25 % to 30 % probability that farm assets will increase in all the scenarios. This means that on average, considering all weather conditions, these farmers are not better-off with insurance because they pay premiums in both good and extreme weather years, and they get payouts only in rare cases of weather shocks.

4. Discussion

4.1. Relevance of the study

While several studies have highlighted different risk management options that can help to stabilize smallholder farmers' income in extreme economic and weather conditions (Findlater et al., 2019; Garrity et al., 2010; Steward et al., 2018; Traore et al., 2017), many smallholding farming households in Northern Ghana are still not able to cope during these harsh conditions as many of them are poor (Appiah-Twumasi et al., 2022; Tsiboe et al., 2023) and their capital assets are eroded (Barnett and Mahul, 2007). As a result, farmers are entangled in poverty traps where they live well below the poverty line, without clearly defined escape routes. Weather-index insurance as a tool to relieve the burden of agro-climatic risks at the farm level (Ricome et al., 2017) have since gained popularity in the literature because it protects farmers' income against crop failure as a result of extreme climatic conditions (Abugri et al., 2017). However, despite the potentials of index insurance, the rate of subscription for these products is still very low with reasons including low awareness and lack of knowledge of the insurance products, unprofitability for the insurance companies, basis risk (Ankrah et al., 2021; Shirsath et al., 2019), and most importantly because many of the insurance contracts are not well enough tailored to suit the needs of the farmers (Sibiko et al., 2018). This has largely led to an abandonment of crop insurance products in Northern Ghana.

This study sheds light and provides valuable insights on the effectiveness of different forms of weather index insurance in stabilizing farmers' income under extreme weather conditions. Notably, the work of Yami and 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 and 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), we tested the impacts of specifically developed weather-index insurance products on farmers' income, evaluating the probabilities of increasing farmers' income. Specifically, we examined

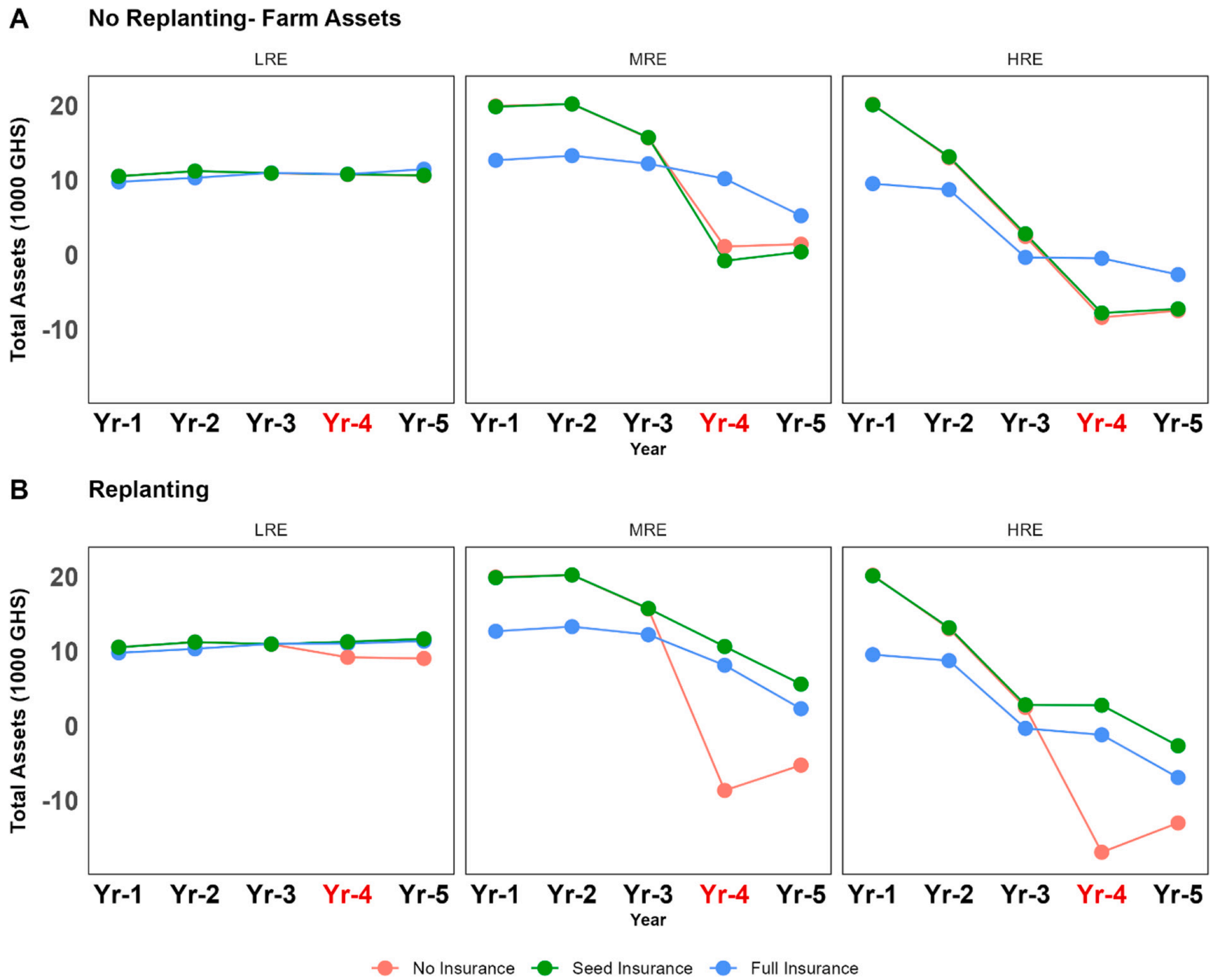

Fig. 4. Time-series of total farm assets. The line plots at the top represents the no-replanting scenarios, while the one at the bottom represents the replanting scenarios. A represents the no-replanting scenarios, while B represents the replanting scenarios. The left plots are for the low resource endowed farms, the middle plots are for the medium resource endowed farms and the right plots 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the effects of purchasing insurance contracts and making decisions regarding replanting in the event of crop failure on farmers' income and how they protect farm assets, especially in extreme weather conditions, considering these factors are key motivations for farmers to purchase insurance contracts (Jensen and Barrett, 2017). Furthermore, the contracts presented here can be adapted to other regions facing predominant risks different from rainfall fluctuations.

By comparing the trajectories of these different scenarios, we identified cost-effective and economically rational risk transfer options for farmers under the region's diverse weather conditions. The results of the 5-year simulation provided valuable insights on the effects of different index insurance and varying farm management practices on farmers' income and assets.

4.2. Insurance- prices and intensification of production

Many studies have examined the willingness to pay for WII by different smallholding farming households, highlighting that farmers reluctance to pay for these products are due high prices (Binswanger-Mkhize, 2012; Vasco et al., 2008). While studies like ShalekBriski et al. (2021) highlight that WII is cheaper than yield based insurance because they reduce administrative cost, however, as seen with the contracts presented in this study, full WII cover might be expensive for these 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 series of good weather years. With an average cost of about 113 GHS ha^{-1} as shown in Table 3, high prices of these insurance contracts are one of the reasons for farmers' low subscriptions in Northern Ghana. However, a good alternative and equally attractive option is the weather index seed insurance option presented in this study, which can enable farmers to replant in times of extreme weather conditions. These insurance contracts are relatively cheaper (about 28 GHS ha^{-1}) since 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 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 presented in this study, promoting weather index seed insurance could be an effective strategy for increasing the subscription rates of insurance in the region since price play a very important role in the demand for index insurance (Clement et al., 2018).

As often suggested in literature, one way smallholder farmers can improve their livelihood is to adopt certain intensification techniques that can increase their crop yields (Chartres and Noble, 2015), by improving their soil fertility (Droppelmann et al., 2016) and water management, consequently 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

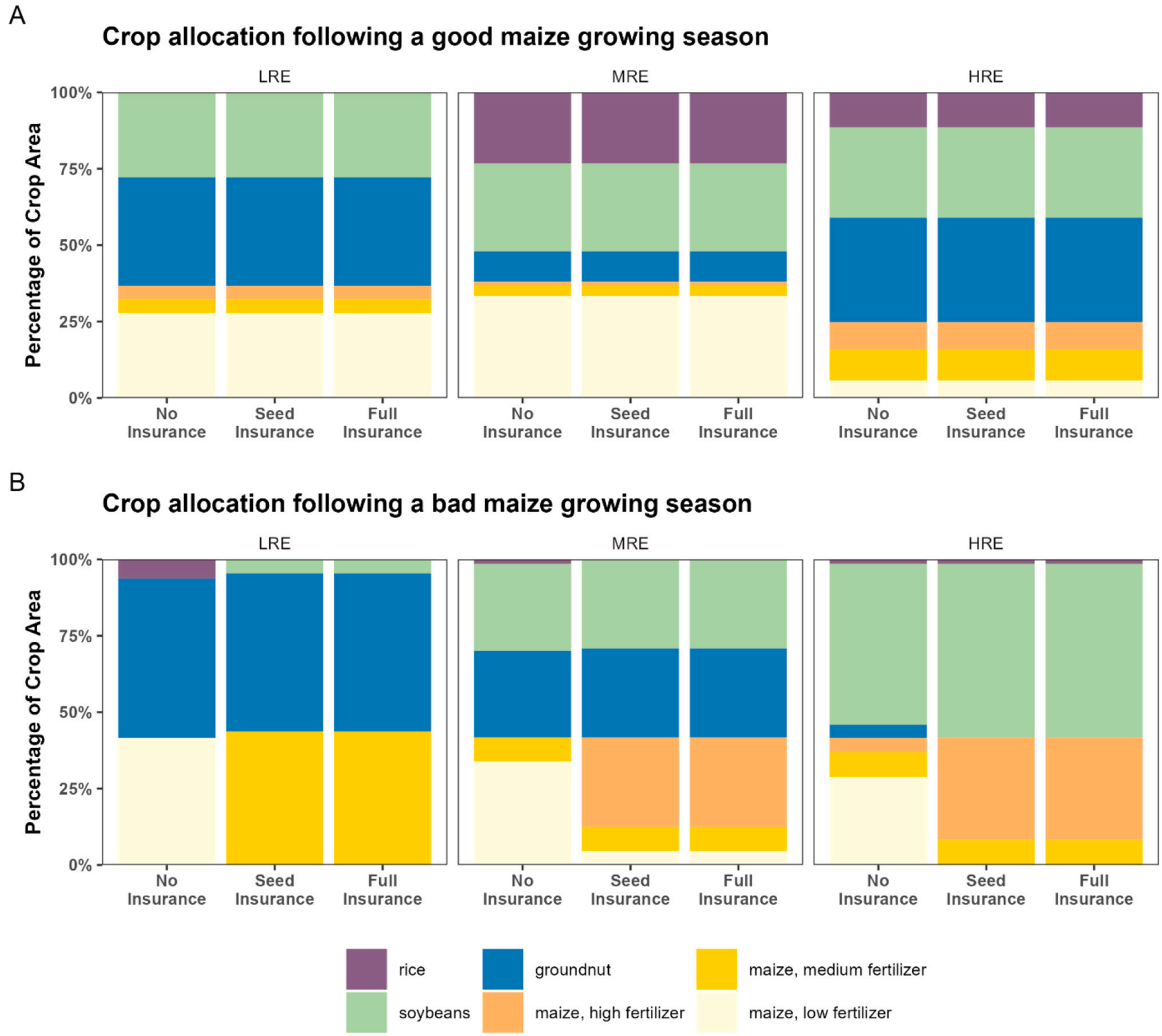

Fig. 5. Cropping activities under different insurance options and replanting scenarios. A- represents results following a good maize growing season. B- represents the results following a bad maize growing season (after a shock year). The left plots are for the low resource endowed farms (LRE), the middle plots are for the medium resource endowed farms (MRE) and the right plots are for the high resource endowed farms (HRE). The purple colour in the bar plot represents the land allocation to rice crop, the blue colour shows the land allocation to groundnut, the green colour shows the land allocation to soybeans, the orange colour shows land allocation to maize crop 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

application of mineral fertilizers (Yami and Van Asten, 2017), which is applied in low quantity in SSA (Pretty et al., 2011). Insurance can 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 expensive for the resource-constrained farmers. 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 and Wiredu, 2017).

4.3. Probability of outcomes under shock- incomes and assets

Farmers' long-term income and livelihood are negatively affected by years of extreme weather conditions (Gadédjiss-Tossou et al., 2016), leading them to seek different forms of alternatives including the need to sell their assets (such as livestock) and leaving them worse-off (Herrero et al., 2013). This study show that farmers are better off purchasing insurance contracts such as seed and full weather index-based insurance 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 index-based insurance during extreme weather events and clamoured for the need to design the contracts based on bigger shocks. Several other studies have also supported this outcome by stressing the importance of WII particularly in extreme weather events (Collier et al., 2009; Greatrex et al., 2015; Jensen and Barrett, 2017; Shirsath et al., 2019). Another interesting aspect of the results presented in this study is that full WII contracts become economically expensive for farmers when they do not experience shocks as seen from the single weather time series effects presented in Fig. 3. This is quite evident considering the overall weather distributions, which leaves farmers worse-off with these insurance options

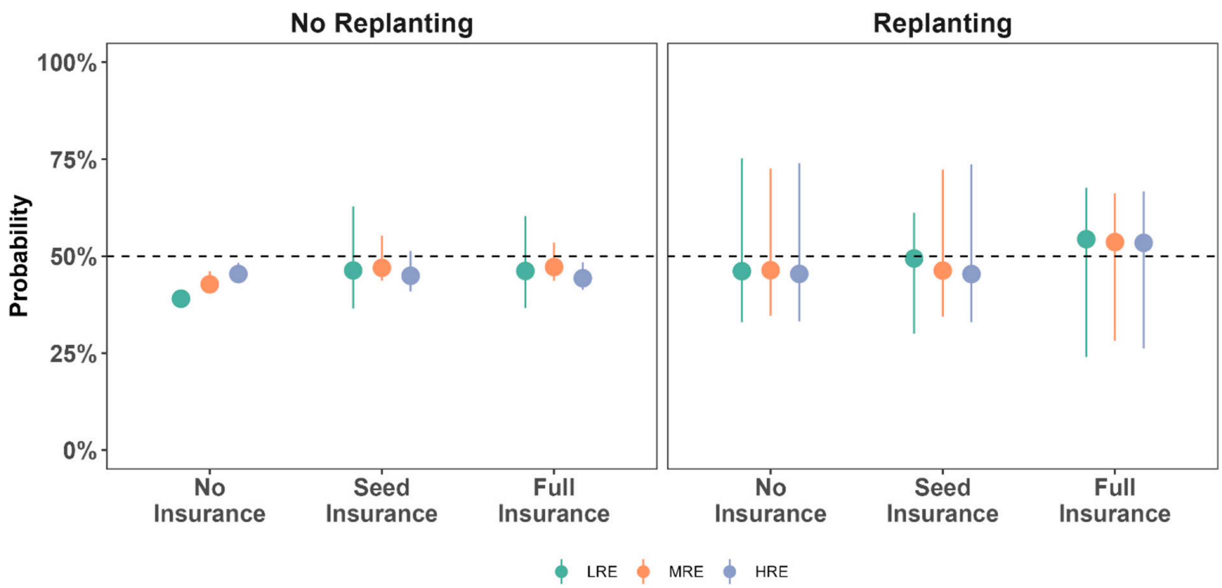

Fig. 6. Probability that farm income increases after 5 years. The probability is obtained by comparing the income in year 2 of simulation to the income in year 5 of simulation. The plot on the left are the results from no-replanting scenario; the plot on the right are the results from replanting scenario. 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 shows the minimum and maximum probabilities respectively. The horizontal dash line shows the 50 % probability line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

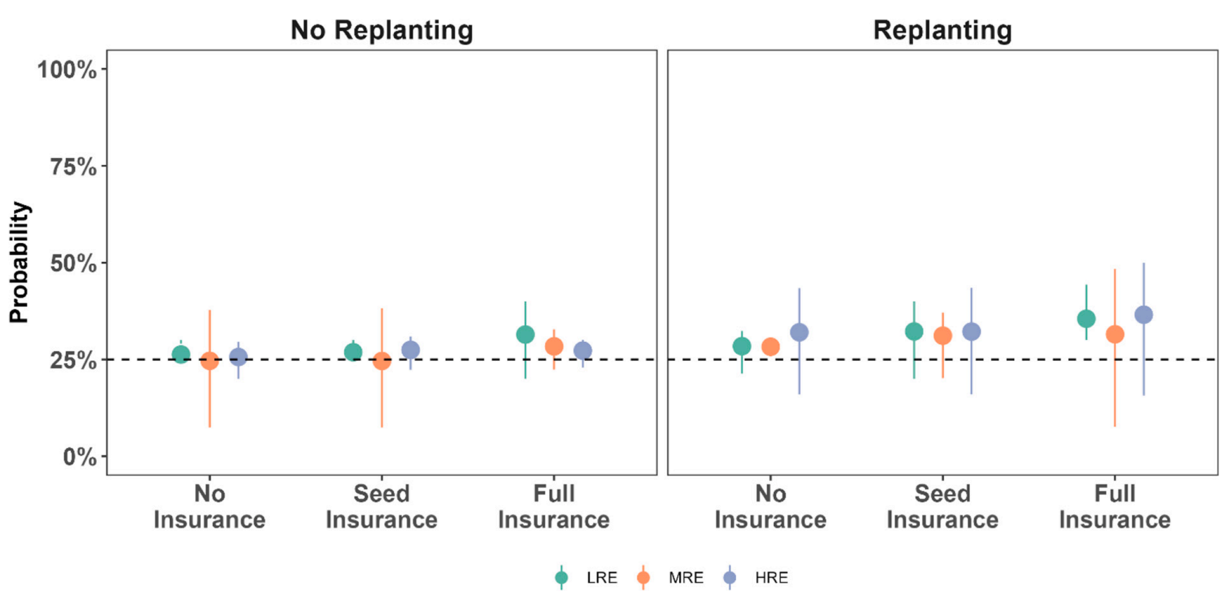

Fig. 7. Probability of farm assets increase after 5 years. Farm assets are defined by the sum of cash value of herd (small and large ruminants) and cash at hand. The probability compared the farm asset at year 2 of the simulation to the farm asset at the end of the simulation (year 5). The plot on the left shows the no-replanting scenario and the plot on the right show 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 shows the minimum and maximum probabilities respectively. The horizontal dash line shows the 25 % probability line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

because extreme weather events do not occur regularly, and farmers must pay premiums each year. This result is particularly important as it further emphasize one of the reasons for 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*".

In addition, as often highlighted in the literature, smallholder farmers are reluctant to purchase insurance contracts unless the premiums are subsidized or the insurance options are coupled with other benefits (Ricome et al., 2017; Sibiko et al., 2018). Included in the insurance contracts in this study, is the benefit of purchasing certified seeds along with the insurance products, which according to Bulte et al. (2020) has been found to increase farmers' adoption rates and incentivised 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 and Miranda, 2015). A resource-constrained smallholder farmer that has already invested so much during this period might be unable to repurchase seeds and other inputs for replanting (Li and Miranda, 2015). Replanting is possible if the farmers purchase index insurances

(Fisher et al., 2019; World Bank, 2015), making the farmers better-off and able to cope better with weather shocks. Results presented in this study show that the WII enables farmers to replant and stabilize their incomes in the event of crop failure during 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 during crop failure can potentially increase equity. However, it is cheaper for the farmers to combine replanting with weather index-based seed insurance contracts than with full WII because with seed insurance, there are no partial payments in the event of indemnities. The payouts are made in full in any event of claim by the farmers. For the full WII, the payout is partially done per crop phase, which makes the payout lower than seed insurance at the same phase.

With food insecurity and poverty highlighted as two of the biggest challenges faced by smallholder farmers in Northern Ghana (Laube et al., 2012; Tsiboe et al., 2023), farmers often struggle to meet their household food and cash requirements especially in extreme weather conditions, leading them to continuously depend on external support for survival (Adelesi et al., 2023). One of the main reasons for the introduction of WII to smallholder farmers is to help them stabilize their income and maintain their livelihood, avoiding poverty traps (Berg et al., 2009). Another key part of the results presented in this study is the consideration for household consumption, which have already been accounted for in all the scenarios, meaning that even if the households have low incomes under certain circumstances, they generally will prioritize meeting their food requirements. This is important because most of the smallholding households are known to consume the majority of their farm produce (Ricker-Gilbert, 2020).

However, as we have shown that extreme weather conditions do not occur yearly, one way to make insurance cheaper for the farmers would be to couple this insurance with other benefits such as incentives on premiums (Adeyinka et al., 2016), subsidies on premiums (Ankrah et al., 2021) or in cases where the premiums are not subsidized, government subsidies can be added to variables like loans, fertilizers (Ricome et al., 2017), or other agronomic inputs (Masiza et al., 2021).

4.4. Challenges of uptake of insurance

Many studies have highlighted that one of the major challenges associated with index insurance is the low rate of uptake (Ankrah et al., 2021; Carter et al., 2014). According to several studies this can be attributed to several factors that include high premiums, lack of government subsidies, lack of trust in the index and even faulty insurance designs (Arshad et al., 2016; Di Marcantonio and Kayitakire, 2017; Ntukamazina et al., 2017). However, as seen from this study, we cannot overlook the effects of income disparity among different farming households. For instance, the farms we presented here range from low to high resource endowed farms, with HRE farms having as much as 2300 GHS cash at the beginning of the season, while LRE having as little as about 126 GHS (Table 3). The likely effect of this is that one of the farms would purchase insurance contracts given the fact that they can afford it compared to another farming household. We show this likely cause of low uptake of insurance with the increasing inequalities among these farm types (see Fig. A2 in Supplementary material). It would however be interesting in a future study to test the factors that might significantly affect the uptake of insurance as this would help to begin to tackle some of the obstacles.

4.5. Study limitations

In contrast to the result of land allocation crops presented in Adelesi et al. (2023) which had the aim to contrast the new integrated annual optimization model with a simulation model with static management, this study applied the new integrated model to address implications of different insurance products on farmers' incomes and assets. While the study was conducted together with colleagues from ACRE Africa to inform the insurance product design, it nevertheless suffered from various shortcomings. This study did not explore the effects of model or spatial basis risk, which could be due to the imperfect prediction of the index or due to imperfection as a result of weather station distance respectively (Leblois et al., 2014). Basis risks are risks associated with crop insurance, where indemnity payments are not triggered in the event of crop loss as a result of faulty design of the insurance contracts and/or incorrect selection of climate variables (Shirsath et al., 2019). By not accounting for basis risk and some possible deviations associated with the index to the farmers' field, there is a high likelihood of over-estimating the gains of the index insurance presented here. To explore the many potential sources of basis risk (e.g., precipitation deviance, assumed sowing dates and soil depths) is clearly required in follow-up studies.

Other factors apart from weather risk that can be associated with losses due to crop failure are not captured in our model and issues regarding the design of the weather index contract could lead to basis risk (Hill et al., 2019). Exploring these options would have further justified this study. In a future study, it would be interesting to account for the effects of basis risk from both the farmer and the insurance company's perspective. In addition, while the crop model can simulate growth under different environmental conditions and management practices, it did not simulate waterlogging, lodging, pests, and diseases conditions, though we did perform an empirical yield reduction to bring yield levels close to reported levels. Another limitation of this study is that we did not simulate for a wide range of planting windows, which can influence grain yield, instead we simulated grain yields for a single planting date and an alternative planting date for the replanting scenarios. Unfortunately, exploring the full range of sowing dates is beyond the scope of the study. However previous studies using large ensemble climate data in West Africa (Faye et al., 2018) demonstrated that the variability of crop yields did not depend on the sowing date across the full weather ensemble. While we recognize it certainly matters on some years, based on the results of Faye et al. (2018) we expect it does not matter appreciably across the very large sample of weather conditions sampled here. In addition, the crop model, as typical of most crop models, has limitations regarding some agronomic practices: first, 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). However, the crop model does not consider yield losses from pests and diseases. Second, wealthy farmers tend to use more improved seeds, such as hybrid maize. However, we have used a single crop parameter set for each crop, meaning that our simulation does 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 and Matusso, 2014), but among nutrient stress, only nitrogen stress is simulated with our crop model. Despite these limitations, our crop model can simulate the main climatic risks in this region: heat and drought. Advancing crop models in simulating diverse management options will help produce more realistic farm simulations, and thus, provide crucial information on designing insurance products.

From the economic side of the model, one major limitation of this study is the assumption of fixed costs and prices. We made this assumption because our large ensemble climate data are simulated data and not actual observed historical data, with different possible combinations of weather variability. Combining these cases to different prices and input costs would call for speculations and unrealistic assumptions due to a lack of data. Furthermore, we did not account for the environmental costs associated with grazing of farm animals. This is because the farmers in the study area practice extensive form of production and no reliable data to account for such costs. We, however, accounted for the associated labour costs for grazing.

Furthermore, we only considered insurance on the 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 on income of a maize insurance product as it is a food crop with 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 are able to introduce insurance for other crops. Additionally, we wanted to limit the complexity of the study to one crop. Finally, soybean is commonly grown in the region under contracts, which preclude the use of an insurance product, though likely with less favourable terms.

Finally, we simulated our model 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, HAPPI dataset comprising 10-yaer time series of 800 members can be used (Mitchell et al., 2017).

5. Conclusions

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 stabilize 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 provider in SSA and testing these contracts along with risk management option of replanting in the case of crop failure on farm income and assets. From this study, it can be concluded that farmers are better-off purchasing seed weather index insurance contracts that enables them to replant in extreme weather conditions and in 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; farmers are, therefore, encouraged to purchase seed weather index-based insurance contracts, which would serve as a means of transferring their risks and increasing their ability to cope with climate and other risks. However, looking at these contracts from a long-term perspective, they become expensive for the farmers as extreme weather conditions do not occur regularly. We, therefore, recommended that insurance options should be bundled with other relief measures such as subsidies on inputs to ease the burden of high cost of insurance on the farmers. In addition, insurance providers should focus first on introducing index insurance contracts for food crops (for example maize as presented in this study) 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 are able to introduce insurance for other crops.

CRediT authorship contribution statement

Opeyemi Obafemi Adelesi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yean-Uk Kim:** Writing – review & editing, Software, Resources, Methodology, Data curation. **Johannes Schuler:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Peter Zander:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Michael Murithi Njoroge:** Methodology, Data curation. **Lilian Waithaka:** Methodology, Data curation. **Alhassan Lansah Abdulai:** Writing – review & editing, Methodology. **Dilys Sefakor MacCarthy:** Methodology. **Heidi Webber:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors express their gratitude to the Leibniz Centre for Agricultural Landscape Research (ZALF) for funding the PhD position, as well as acknowledge support from the German Ministry of Education and Research (BMBF grant 01LL2204B); the Leibniz Association Female Professorship award (P102/2020); and the support of the Capacitating African Smallholders with Climate Advisories and Insurance Development project (CASCAID) project.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.104130.

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