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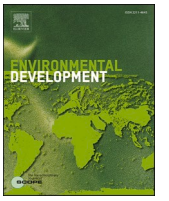

Enhancing climate resilience in northern Ghana: A stochastic dominance analysis of risk-efficient climate-smart technologies for smallholder farmers

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ABSTRACT

Northern Ghana is a semi-arid region characterised by a unimodal rainfall pattern, and hot and dry weather conditions. Heavy reliance on rain-fed agriculture and the lack of resources for irrigation, makes smallholder farmers in the region increasingly vulnerable to climate-related crop failures. In recent years, climate-smart technologies (*CSTs*) such as changing planting dates (*PD*), compartmental bunding (*CB*), mulching (*M*), and transplanting (*TP*) have been recommended to minimise yield losses. However, there is limited information on the most risk-efficient *CSTs* for crops cultivated in the region. This study used a stochastic dominance approach to identify the most risk-efficient *CSTs* for maize, rice, and sorghum. The stochastic modelling process employed the Aqua-crop model to simulate climate-related yield variability using Ghana climate data, and gross margin variability with crop budgets from literature sources. From the study's findings, changing planting date from April to May was the most risk-efficient choice for maize and sorghum under farmers' and recommended practices. In contrast, transplanting was the most risk-efficient technology for rice farming in the study area. The study also highlights the importance of considering the risk-averse nature of smallholder farmers when selecting *CSTs*. By identifying the most risk-efficient *CSTs*, the study can help improve the resilience of smallholder farmers. These findings have important implications for the development and adoption of *CSTs* in northern Ghana.

1. Introduction

As smallholder farmers in developing countries continue to depend on rainfed agricultural systems, climate variability, such as temperature and precipitation changes, significantly impacts their decision-making processes (Bhave et al., 2016). Wossen et al. (2014) indicate that such changes in temperature and precipitation could have dire implications on the food security and economic wellbeing of smallholder farm households. According to Issahaku and Abdulai (2020), the high level of climate variability in the last 40 years has created uncertainty in the agricultural production system, exposing poor farmers to higher crop production risk. Climate risk vulnerability in developing countries has been attributed to the high level of poverty, resource constraints, low adaptive capabilities as a result of the lack of adequate infrastructure and technology, and weaknesses in institutional frameworks (Serdeczny et al., 2017).

To enhance climate risk resilience, climate-smart technologies such as changing planting dates, drought-resistant crop varieties,

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irrigation, and soil water conservation technologies have been employed in developing countries to improve crop yield (Di Falco and Veronesi 2013; Adamson et al., 2017). According to the Food and Agricultural Organisation (FAO), a climate smart technology is described as an activity that enhances the productivity and profitability of farms, increases resilience to climate change, and reduces environmental impact (Issahaku and Abdulai, 2020).

Various studies such as Abegunde et al. (2019), Antwi-Agyei et al. (2021), Chinseu et al. (2018), Dougill et al. (2021) and Makate (2019), have highlighted the importance of *CSTs* in improving food security in developing countries. However, there are some notable trade-offs associated with using some of them. For example, mixed cropping is a climate smart technology that is capable of improving the adaptability of smallholder farmers by increasing their income and reducing production risk relative to growing a single crop; however, it may result in over-crowding, reduction in soil nutrients, and may eventually cause land degradation (Antwi-Adjei et al., 2023). Also, irrigation methods are helpful in reducing yield losses, but such technologies are likely to be expensive for smallholder farmers.

Several research institutions in Ghana, such as the Centre for Scientific and Industrial Research, Universities, and the Ministry of Food and Agriculture, have developed climate smart technologies to support farmer adaptation to climate change. According to Nakuja et al. (2012), climate smart technologies in northern Ghana include but are not limited to tree planting, irrigation, early maturing and drought tolerant varieties, conservation agriculture, row planting, inorganic fertilizers, and high-yielding varieties. Promoting climate smart technologies in Ghana under the National Climate Smart Agriculture Program and the Food Security Action Plan has created a roadmap to scale up the adoption of climate smart intervention activities in all agroecological regions countrywide (Essegbey et al., 2015). Despite these initiatives, the level of climate smart technology adoption is low (Barasa et al., 2021; Djido et al., 2021). This increases the exposure of smallholder farmers to production risk under increasing climate variability.

Issahaku and Abdulai (2020), revealed using climate smart technologies such as drought-resistant and early maturing varieties along with soil and water conservation results in increased income and reduced exposure to production risk. Given the importance of climate smart technologies for risk management, it is crucial to analyse this from the perspective of the smallholder farmer's risk preference. However, there is a lack of research in northern Ghana on the connection between using climate smart technologies and smallholder farmers' risk preferences. This study intends to contribute to closing the gap by analysing how risk-efficient climate smart technologies, namely changing planting date, transplanting, mulching, and compartmental bunding, are from the perspective of risk aversion among smallholder farmers, using a stochastic dominance approach.

2. Stochastic dominance modelling

Several studies have been conducted on risk ordering with stochastic dominance (Anderson, 1974; Hardaker et al., 2015). These studies explained the preference assumption and ordering rules for first and second-order stochastic dominance. From their findings, for first-order stochastic dominance *(FSD)*, the decision maker prefers more to less of the random variable, such as gross margin *(GM)*. In the current study, this implies that smallholder farmers want to maximise their satisfaction when using *CSTs*. So in selecting the most risk-efficient *CST*, they will eliminate alternatives with high probabilities of low *GM* outcomes. For two technologies *X* and *Y*, each with a distribution of *GM* outcomes defined by Cumulative Distribution Functions (*CDFs*), $F_X(GM)$ and $F_Y(GM)$, respectively, technology X dominates Y in the first-degree sense if and only if: $F_X(GM) \leq F_Y(GM)$ and $F_X(GM) < F_Y(GM)$ for at least one *GM* outcome (Anderson, 1974). For the *FSD* condition, $F_X(GM)$ graphically falls below $F_Y(GM)$ (Fig. 1). Also, FSD is transitive, in the sense that when another

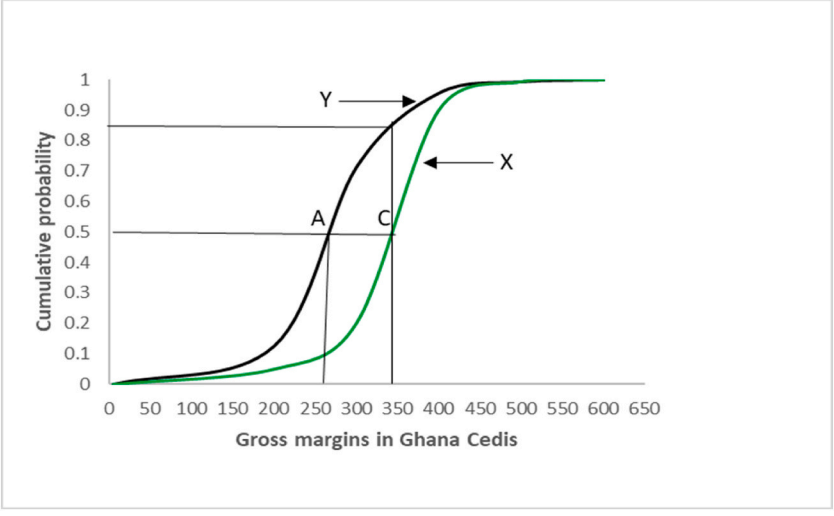

Fig. 1. Cumulative distribution functions *(CDFs)* for technologies *X* and *Y* showing first-order stochastic dominance.

alternative *(Z)* is included, one can conclude that if $F_X(GM) \leq F_Y(GM)$, and $F_Y(GM) \leq F_z(GM)$, then $F_x(GM) \leq F_z(GM)$ (Bezuneh, 1992).

The *CDFs* in Fig. 1 show the probability of an event occurring at a point or at an interval. The 0.5 and 0.85 cumulative probabilities imply that the probability of receiving between 0 and 350 Ghana cedis (GH₵) at point C is 50% for technology *X* and 85% for technology *Y* respectively (Fig. 1). This means, relative to technology *X*, there is a high probability of achieving a low *GM* outcome when technology *Y* is used as both cumulative probabilities (i.e. 0.5 for *X* and 0.85 for *Y*) occur at an interval of GH₵ 0 to GH₵ 350. Alternatively, at a cumulative probability of 50% (0.5) for both technologies, farmers receive between GH₵ 0 to GH₵ 350 (point C) for using technology *X*, but only GH₵ 0 to GH₵ 250 (point A) using technology *Y*. A rational smallholder farmer who prefers more to less will always choose technology *X* over *Y*.

To tie in the concept of risk aversion, second-degree stochastic dominance (*SSD*) is employed when the cumulative distributions of the technologies cross (Fig. 2). In Fig. 2, technology *X* dominates *Y* at lower regions of *GM* (i.e. between *D* and *E*). In contrast, at higher regions between *E* and *F*, technology *Y* dominates *X*, violating *FSD*. *SSD* approaches this by searching for the undominated option from these alternatives using the area under the curve of the *CDF* for all levels of *GM* outcomes for those technologies (Hardaker et al., 2015). The technology with the smallest area under the curve represents the most preferred option for a risk-averse farmer, given that the farmer's utility is monotonically increasing at a decreasing rate. This is mathematically expressed as:

$$\int_{-\infty}^{GM} F_X(GM)dGM \leq \int_{-\infty}^{GM} F_Y(GM)dGM \tag{1}$$

Where $-\infty$ to *GM* represents the *GM* range from negative infinity $(-\infty)$, which is the lowest *GM* to the highest for technology *X* and *Y*, respectively. From equation (1), $F_X(GM)$ second-order stochastically dominates $F_Y(GM)$.

Research institutions in Ghana have recommended many climate smart technologies, but there is a lack of research-led evidence on which *CSTs* are the most risk-efficient ones within the framework of the smallholder farmer's expected utility. As a result, the objective of this research is to determine whether climate smart technologies in northern Ghana produce higher yields, how risky the use of climate smart technologies are in northern Ghana, which climate smart technology is risk efficient, and to investigate if farmers are better off financially from adopting them.

3. Study area

The study area is made up of 25 communities from the Savelugu-Nanton, West Mamprusi and Tolon Kumbungu districts and is situated in the Guinea savannah agro-ecological zone of northern Ghana with Tamale being the regional capital (Fig. 3). Soil types in the region are predominantly Savanah Ochrosols (Mustapha et al., 2020) with a land area of approximately 70,383 km^2 representing about one-third of Ghana's land area (Mustapha et al., 2020). Northern Ghana is the leading producer of most grains and cereals in Ghana including maize, rice, and sorghum (Yiridoe et al., 2006). About 90.5% of the households are rain-fed crop farmers with limited capacity to mitigate the negative effects of climate variabilities due to low socio-economic development, resulting in major adverse impacts on crop yield (Antwi-Agyei et al., 2012).

The rainfall season in northern Ghana begins in April/May and ends in September/October each year. Northern Ghana is the most climate-vulnerable region in the country (Amikuzino and Donkoh, 2012) and is characterised by an uni-modal rainfall pattern. The rainfall pattern in the region usually peaks in September, followed by a subsequent decline from October to January (Appendix 1). The

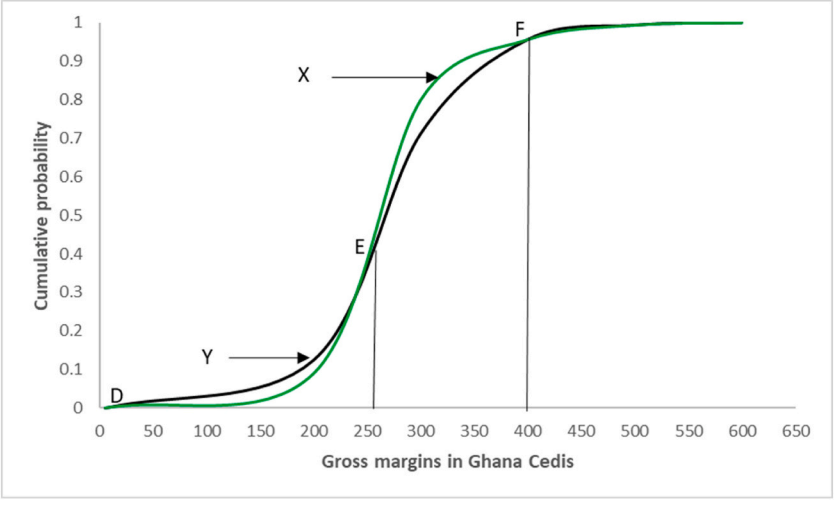

Fig. 2. Cummulative distribution functions *(CDFs)* for technologies *X* and *Y* showing second-order stochastic dominance *(SSD)*.

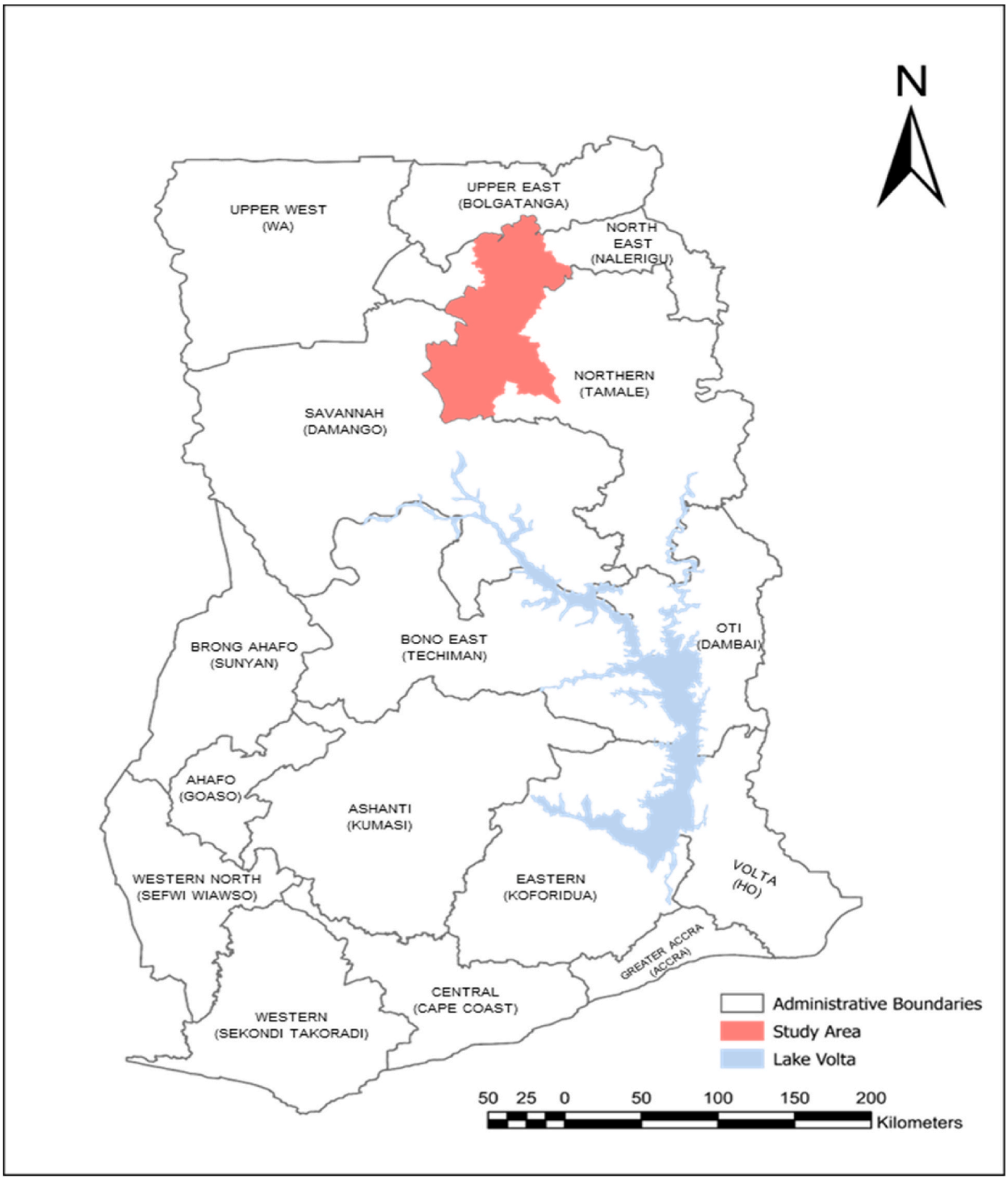

Fig. 3. Map of Ghana showing regions and regional capitals

mean monthly rainfall recorded from November to March usually falls below 50 mm/month, with December and January experiencing almost 0 mm of rain (Appendix 1). Although there are episodes of rainfall from November to March, there is a prolonged drought before the beginning of the April/May rainy season, which records beyond 50 mm of rain/month. Hence, the cropping season for most crops in the Guinea Savannah zone for northern Ghana starts in April/May each year (FAO, 2020).

4. Method of analysis

4.1. Aquacrop simulation

To estimate the appropriate gross margin distributions for stochastic dominance modelling, this research uses Aquacrop models to simulate yields for three main crops cultivated in the study area (i.e. maize, rice, and sorghum) given the soil type, climate smart technologies, farmers' practice and recommended practice. In the current study, farmers' practice refers to nitrogen application rates generally practiced by farmers in the study area, whereas recommended practice refers to recommended nitrogen application rates/crop from literature sources such as MacCarthy et al. (2017), MacCarthy et al. (2010), and Ragasa et al. (2013). The structure and flow of this modelling process is illustrated in Fig. 4. The following subsections describe the process in detail.

4.1.1. Soil

The soil type in the study area is characterised by moderately coarse fragments (Tetteh et al., 2016). Data on soil profile was collected from Tetteh et al. (2016) by taking the percentage of sand, silt, clay, and organic matter (*OM*) in g/kg of soil in the study area. The United States Department of Agriculture (*USDA*) soil hydraulic properties calculator converts the soil profile data comprising 124 g (*OM*)/kg of soil, and soil with 45% sand, 51% silt, and 4% clay to Aquacrop-useable parameters. The results indicate that the soil properties formed a silty loam textural class at a permanent wilting point (*PWP*) of 3.5 %Vol, field capacity (*FC*) of 16.7 %Vol, saturation point (*SAT*) of 35 %Vol, total available water (*TAW*) of 98.3 mm/m and a saturated hydraulic conductivity (Ksat) of 378 mm/day. These soil profile parameters were used to run all crop simulations in Aquacrop.

4.1.2. Climate

Aquacrop requires daily climate data on rainfall, minimum and maximum temperature, solar radiation, wind speed, and relative humidity to calculate evapotranspiration and consequently simulate crop yield and biomass production. Climate data from 1st January 1990 to 31st December 2020 was downloaded from the National Aeronautics and Space Administration's POWER (Prediction of Worldwide Energy Resources) database (NASA, 2023) using the GPS coordinates of the study area. In addition, the research utilised the Aquacrop in-built carbon dioxide (CO_2) concentration data from the Mauna Loa Observatory Laboratory in Hawaii.

4.1.3. Crops

4.1.3.1. Maize. Aquacrop has an in-built maize-calibrated module suitable for all growing conditions. However, the current study seeks to achieve simulated yields using conditions similar to northern Ghana: soil type, climatic conditions, and cultivar. As there is no Aquacrop appropriate experimental data for maize in northern Ghana, the study utilised Aquacrop parameters and field experiments conducted by Akumaga et al. (2017) at the Institute of Agricultural Research, Ahmadu Bello University, located in Zaria, northern Nigeria. This was a seven-year experiment from 2007 to 2013 for a hybrid maize cultivar (Oba Super 2 variety) used to calibrate maize

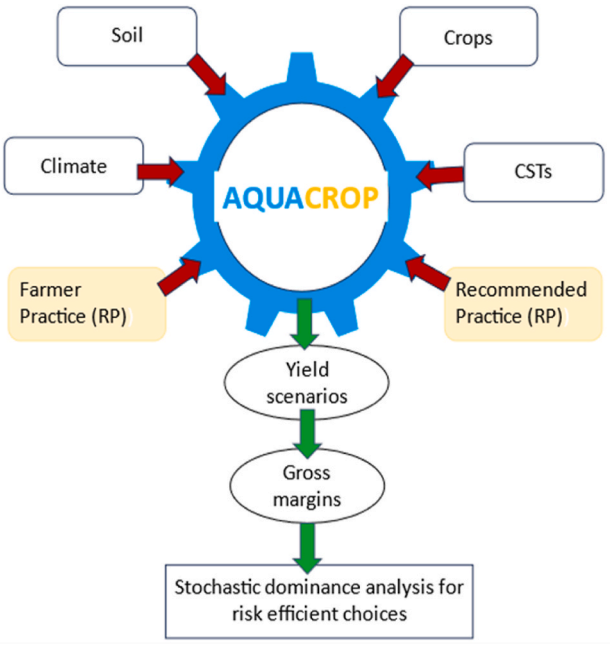

Fig. 4. Modelling framework for stochastic dominance analysis.

in Aquacrop under local soil and environmental conditions. The Aquacrop model simulations from the research were validated against observed yield using the root mean squared error (*RMSE*) method.

The parameters from Akumaga et al. (2017) were modified to suit growing conditions in northern Ghana. The current study employed Aquacrop generated planting dates, which are chosen based on the soil and climatic conditions each year in northern Ghana. To effectively account for variations in temperature and the effect of thermal time on crop growth and development, the study runs the model on a growing degree day (*GDD*) mode instead of calendar days by switching to the growing degree days option in Aquacrop (Karunaratne et al., 2011). In addition, calendar days have been described as an inappropriate way of examining crop phenology since water stress which is often affected by temperature, has a crucial effect on flowering and physiological development of the crop (Azam-Ali and Squire, 2002). As a result, calendar-days data from Akumaga et al. (2017) was imported into Aquacrop and converted to *GDD* units using climate and soil data from northern Ghana. The data generated for northern Ghana in growing degree days (*GDD*) is represented in Appendix 2.

4.1.3.2. Sorghum. To the best of our knowledge, no Aquacrop-appropriate experimental data was available for sorghum for Sub-Saharan Africa. As a result, sorghum yield simulations were modelled using the Aquacrop default sorghum file under the study area's climatic and soil conditions used to simulate maize. The variety calibrated in Aquacrop is the Texas Bushland sorghum variety. Appendix 3 represents the parameters for simulating sorghum yield in Aquacrop. The time from sowing to emergence, maximum rooting depth, canopy senescence, maturity, flowering duration, and building of harvest index were recorded in growing degree days for reasons explained earlier.

4.1.3.3. Rice. Following the calibration and yield simulation for maize and sorghum, the Aquacrop rice model was also calibrated for northern Ghana based on data from available literature. Data on soil profile and climate were retained in the Aquacrop model. The parameters in the Aquacrop default rice file were updated using the Abdul-Ganiyu et al. (2018) crop parameter data already validated for the Aquacrop rice model for northern Ghana (Appendix 4). However, unlike the current study, where rice yield is modelled under rainfed conditions, Abdul-Ganiyu et al. (2018) calibrated Aquacrop rice under irrigation at the Savannah Agricultural Research Institute in northern Ghana. The Gbewa Jasmine 85 rice variety was used for the simulation. This variety was experimented in the study area during the 2012/2013 and 2013/2014 dry seasons.

4.2. Generating gross margins (GMs)

Aquacrop yields over the 31 years were used to generate gross margins for cropping activities using equations (2)–(4). In the current study, all economic variables are measured in GH₵ at the current exchange rate of 1 GH₵ to 0.15 NZD (New Zealand Dollars) and 0.087 USD (United States Dollars). Prices were obtained from the FAO annual crop prices database. Further, the FAO producer price index was used for inflation adjustment. All prices including that of crop budgets were converted to 2020 real prices using equation (2).

$$RP_{it} = \frac{PPI_{ic}}{PPI_{it}} \times NP_{it} \tag{2}$$

where:

RP_{it} = Real price/tonne (GH₵) for the i^{th} crop in year t
PPI_{ic} = Producer price (GH₵) index for the i^{th} crop in the base year (2020)
PPI_{it} = Producer price (GH₵) index for the i^{th} crop in year t
NP_{it} = Nominal price/tonne (GH₵) for the i^{th} crop in year t

The GMs derived are expressed in equation (3) as:

$$GM_{it} = R_{it} - C_i \tag{3}$$

where:

$$R_{it} = RP_{it} * Q_{it} \tag{4}$$

R_{it} = Revenue (GH₵/Ha) for the i^{th} crop in year t
Q_{it} = Yield (tonnes/Ha) for the i^{th} crop produced in year t
C_i = The cost of production (GH₵/Ha) incurred for the i^{th} crop
GM_{it} = Gross margin (GH₵/Ha) for the i^{th} crop in year t

As data on labour requirements is scanty (i.e. both family and hired labour) for the specific fertiliser application rates among smallholder farmers, the cost of production/hectare including extra labour requirements for each practice, was extrapolated on pro-rata basis mainly from Wongnaa et al. (2019), Akuriba et al. (2011), and Akolgo (2021) for maize, sorghum, and rice crops respectively (Appendices 5, 6 and 7). The labour requirements for maize under farmers practice without climate smart technologies was 66.8 person-days/Ha, whereas recommended practice was 99.8 person-days/Ha. This represents a total of 33 person days required to change from farmers' practice to recommended practice without climate smart technologies. For sorghum, an extra labour of 88.4 person-days is required to change from farmers' practice (i.e., 0 kgN) to the recommended practice of 80 kgN, whereas, rice under farmers' practice requires an extra labour of 42.5 person days/Ha to change to recommended practice. By introducing climate smart

technologies for each practice, an average of six person-days/Ha (Baijuka et al., 2005), 10.5 person days per Ha (Zemadim et al., 2014), and 21 person-days/Ha (Jakada and Ifyalem, 2023) are required for mulching, compartmental bunding, and transplanting, respectively. As per our 2020 real price calculation in equation (2), labour cost from Wongnaa et al. (2019) was priced GH₵ 8/person-day. Further, although the cost of labour is a challenge for smallholder resource poor farmers (Dzanku and Tsikata (2022), we confirm the availability of family and hired labour in the study area as indicated in Akuriba and Brempong (2011) and have included labour cost in calculating our gross margins. However, as farmers do not pay family members for their labour, the cost of hired labour was retained for that of family labour. As a result, family and hired labour were both valued same at GH₵ 8/person-day.

4.3. Model Simulation

Having calibrated the model, the study addressed the research questions by simulating crop yield for maize, sorghum, and rice from 1990 to 2020. The Africa RISING survey revealed that farmers used on average, 27 kg/Ha and 28 kg/Ha of nitrogen for maize and rice, respectively. MacCarthy et al. (2017) confirmed that most farmers on average apply less than 30kg/Ha of nitrogen for maize farming in northern Ghana. However, farmers in the region do not often use fertilizers for cultivating sorghum (MacCarthy et al., 2010). The recommended nitrogen (N) application rates for maize, sorghum, and rice are 60 kgN/Ha (MacCarthy et al., 2017), 80 kgN/Ha (MacCarthy et al., 2010), and 60–80 kg N/Ha (Ragasa et al., 2013) respectively. In the current study, the application rates for farmers' practice were 30 kgN/Ha, 0 kgN/Ha, and 28 kgN/Ha for maize, sorghum, and rice, respectively, whereas recommended practice was 60 kgN/Ha for both maize and rice and 80 kgN/Ha for sorghum. For each farmer practice and recommended practice, four scenarios were modelled for maize and sorghum, starting from planting in April with no climate smart technology (*Base*), changing planting date (*PD)* from April to May, mulching *(M)*, and compartmental *(CB)* (Table 1). However, as rice is cultivated in June, which is almost close to the peak of the rainy season, only direct planting (*DP*), transplanting *(TP)*, and changing planting date *(PD)* from June to July were modelled for both farmers' practice and recommended practice.

Further, for each scenario, the time series yield data from the simulations per crop were converted to gross margins through the previously discussed procedure for generating gross margins. The gross margin outcomes are then used to generated cumulative probabilities. The cumulative probabilities are plotted against the gross margin outcomes from the lowest to the highest gross margin for all scenarios per crop to produce cumulative distribution functions. The area under the cumulative distribution functions for each crop will be calculated and the smallest selected as the most preferred scenario for smallholder farmers. All biophysical and statistical computations were completed in Aquacrop version 6.1 (Raes et al., 2017) and R version 4.2.3 (R Core Team, 2023) respectively.

5. Results and discussion

5.1. Yield

5.1.1. Maize

Average maize yield results under farmers' practice were 1.88 tonnes/ha, 1.91 tonnes/ha, 1.89 tonnes/ha, and 1.96 tonnes/ha for no climate smart technology (Base), mulching (M), compartmental bunding (CB), and changing planting date (PD), respectively (Appendix 8). These results are similar to the average yield of Wongnaa et al. (2019) at 1.8 tonnes/Ha for a 2015 field survey on smallholder farming communities in northern and southern Ghana. However, under recommended practice, the average yields for mulching, compartmental bunding, and changing planting date were 3.47 tonnes/Ha, 3.50 tonnes/Ha, and 3.57 tonnes/Ha, respectively, whereas that of no climate smart technology(base) was 2.81 tonnes/Ha, which corresponds with the 2.72 tonnes/Ha average yield reported by Essel et al. (2020) for maize in Ghana when 60 kg/Ha of nitrogen was applied. In the current study, the coefficient of variation is also used as a measure of variability. This implies that yield variability reduced from no climate smart technology (*Base)* to changing planting date (*PD)* for both farmer practice *(FP)* (i.e. from 7% to 2%) and recommended practice (*RP)* (i.e. from 12% to 3%) (Appendix 9), representing a 71.4% and 75% reduction in variability for both *FP* and *RP,* respectively. The coefficient of variation under *RP* for *Base* represents a 45.5% reduction in variability when compared to the 22% coefficient of variation reported by MacCarthy et al. (2018) at an application rate of 120 kgN/Ha under rainfed conditions in Yendi.

5.1.2. Sorghum

For Sorghum under farmers' practice, since no fertiliser was applied, as is the usual practice of smallholder farmers in the region, the yield was low on average, and there was little difference in average yield for *Base* and climate smart technologies. On average, yield

Table 1
Practices and scenarios simulated.

Crop	FP (N kg/ha)[2]	RP (N kg/ha)[2]	Scenarios
Maize	30	60	Planting in April with no CST (*Base*), Changing planting date from April to May (*PD*), Mulching (*M*), Compartmental bunding (*CB*)
Sorghum	0	80	
Rice	28	60	Direct planting (*DP*), Changing planting date from June to July (*PD*), Transplanting (*TP*)

[2]FP(N kg/ha) = Farmers' practice for nitrogen application rates in kilograms/hectare and RP(N kg/ha) = Recommended practice for nitrogen application rates in kilograms/hectare.

for farmers' practice across all scenarios was 0.82 tonnes/Ha, which is in line with the 0.71 tonnes/Ha and 0.61 tonnes/Ha reported by Kpongor et al. (2006) and Akuriba et al. (2011) respectively. Specifically, *Base,* mulching *(M),* compartmental bunding *(CB)*, and changing planting dates (*PD)* yielded 0.81 tonnes/Ha, 0.82 tonnes/Ha, 0.82 tonnes/Ha, and 0.83 tonnes/Ha, respectively under *FP* (Appendix 8). The coefficient of variation reduced from 5% for *Base* to 4% for climate smart technologies *(i.e. M, CB, PD),* representing a 20% reduction in variability.

Under recommended practice, the coefficient of variation reduced from 23% for *Base* to 11% for changing planting date*,* representing a 52.2% reduction in variability. The average yield for sorghum under *Base* was 2.61 tonnes/Ha, whereas that of *M, CB,* and *PD* recorded 2.76 tonnes/Ha, 2.61 tonnes/Ha, and 2.84 tonnes/Ha, respectively (Appendix 8). Similarly, studies conducted by Kpongor et al. (2006) revealed sorghum yield for northern Ghana at 2.86 tonnes/Ha when 80 kg N was applied. From the results of this study, changing planting date had the highest yield and lowest variability for both farmers' practice and recommended practice, as is the case for maize.

5.1.3. Rice

As rice production occurs close to the peak of the rainy season, climate variability did not reflect across the climate smart technology scenarios for both farmers' practice and recommended practice. Under farmers' practice, average rice yields for direct planting and changing planting date were 3.03 and 3.07 tonnes/Ha, respectively, but increased to 3.21 tonnes/Ha when transplanted. On the other hand, yield for recommended practice increased on average from 4.79 tonnes/ha for direct planting (*DP*) to 4.83 tonnes/ha for changing planting date(*PD*) from June to July and further increased to 5.06 tonnes/ha for transplanting (*TP)* (Appendix 8). This implies that growing transplanted seedlings benefits farmers under both practices, albeit marginal.

5.2. Gross margins (GMs)

The study included cost of land preparation, pesticides, seed, and fertilisers (Appendix 5 to 7) to account for the different cost components required to generate gross margins under farmers practice and recommended practice. Cost of nitrogen requirement per practice is calculated based on the price of NPK at 15:15:15, as this is the fertiliser mainly used by Ghanian farmers (Chapoto and Tetteh, 2014). Further, manual labour cost per person day for application of fertiliser and pesticide, weeding, transportation, harvesting, processing, bagging, and threshing were included. From these cost computations, the difference between total cost and average total revenue based on the product of average yield and the average price/ton for each crop from 1990 to 2020 was calculated to derive gross margins. The crop specific results are presented in Appendix 8.

5.2.1. Maize

Average maize gross margin (*GM*) under farmers' practice (*FP*) as indicated in Appendix 8 was 813 GH₵/Ha for no climate smart technology *(Base)*, 755 GH₵/Ha for compartmental bunding *(CB*), and 902 GH₵/Ha for changing planting date *(PD)* which resonates with the 948 GH₵/Ha and 510 GH₵/Ha reported by Bidzakin et al. (2014) and Wongnaa et al. (2019), respectively. However, mulching *(M)* resulted in the lowest gross margin (i.e. 223 GH₵/Ha) under *FP* as a result of the high cost of mulching at 588 GH₵/Ha (Anane et al., 2020), plus the extra labour cost required to mulch. The findings of Anane et al. (2020) reveal that farmers were better off growing maize without maize straw mulch when a cost-benefit analysis for maize cultivation under organic mulching and intercropping was conducted. On the other hand, cultivating using recommended practice *(RP)* produced an increase in *GM* from no climate smart technology (*Base)* to mulching *(M),* compartmental bunding *(CB)*, and changing planting date *(PD)* with these being 1278 GH ₵/Ha, 1358 GH₵/Ha, 1935 GH₵/Ha, and 2605 GH₵/Ha, respectively (Appendix 8). Also, *GM* coefficient of variation under *RP* reduced from 43% for *Base* to 23% for *PD,* representing a 46.5% reduction in variability due to implementing a climate smart technology *(CST)* (Appendix 9).

5.2.2. Sorghum

Under farmers' practice (*FP)*, average gross margin (*GM)* for sorghum was 521 GH₵/Ha, −99 GH₵/Ha, 479 GH₵/Ha and 559 GH ₵/Ha for *Base, M, CB,* and *PD,* respectively (Appendix 8). The average sorghum *GM* for *RP* was 3191 GH₵/Ha, 2845 GH₵/Ha, 3108 GH ₵/Ha, and 3635 GH₵/Ha for *Base, M, CB,* and *PD*, respectively. The low *GM* for *M* for both practices is due to previously discussed reasons regarding cost of mulch. Also, the sorghum *GM* variability reduced from *Base* to *PD* by 12.8% and 35% under *FP* and *RP* respectively.

5.2.3. Rice

The average gross margin (*GM*) for rice under farmers' practice *(FP)* was 5,187 GH₵/Ha using the direct planting *(DP)* method whereas changing planting date *(PD)* and transplanting *(TP)* were 5261 GH₵/Ha and 5505 GH₵/Ha, respectively. On the other hand, the gross margin *(GM)* for rice on average for recommended practice *(RP)* increased beyond *FP* to 8198 GH₵/Ha, 8259 GH₵/Ha, and 8710 GH₵/Ha for *DP, PD*, and *TP,* respectively (Appendix 8). This implies that for both practices, *TP* remained profitable given the differences in *GMs* for *DP* and *PD*. Also, regarding the variability, the coefficient of variation varied from *DP* to *TP* at 13.3% and 0.07% for *FP* and *RP* respectively (Appendix 9).

5.3. Cumulative distribution functions (CDFs) and stochastic dominance

Based on the *GM* outcomes, cumulative distribution functions *(CDFs)* for *Base* and each climate smart technology *(CST)* were

plotted to determine first order stochastic dominance (FSD) and second order stochastic dominance (SSD). The findings for the total area under the *CDFs* are presented in Table 2, being a product of the change in *GM*, and the corresponding cumulative distribution accumulated from the lowest *GM* to the highest *GM* for *Base* and all *CSTs*. The scenario with the smallest area under the *CDFs* per practice for each crop is selected as the less risky one and most dominant by SSD.

5.3.1. CDFs for maize GMs

Under *FP*, *CB*,*Base*, and *PD* were first-order stochastically dominant over *M* as their curves are completely to the right of *M* making all *GM* probability outcomes from the lowest to the highest *GM* for no climate smart technology (*Base),* compartmental bunding *(CB),* and changing planting date (*PD)* better than mulching (*M)* (Fig. 5). In Table 2, for *FP*, $PD < Base < CB$ implying that the area under the curve for *PD* is the least so *PD* dominates *Base* and *CB*, by second order stochastic dominance (*SSD)*. Furthermore, under recommended practice *(RP),* $PD < CB < M < Base,$ hence *PD* dominates all climate smart technologies *(CSTs)* including *Base* by *SSD*.

5.3.2. CDFs for sorghum GMs

The *CDFs* for sorghum followed a similar trend to maize for *FP*. From Fig. 6, under *FP, Base, CB,* and *PD* were first-order stochastically dominant over *M* for reasons previously explained, and from Table 2, *PD* dominates *Base* and *CB* by *SSD* as $PD < Base < CB$. Similarly, under *RP,* $PD < Base < CB < M$ by *SSD* (Table 2), indicating that *PD* is first-order stochastically dominant over all *CSTs* including *Base*, which implies that, relatively, the *GM* outcomes for *PD* are strictly better for at least one outcome, hence the most preferred.

5.3.3. CDFs for rice GMs

From Fig. 7, the area under the *CDFs* for both practices for rice revealed that *TP* is second order stochastically dominant over changing planting date (*PD)* and direct planting (*DP)* as the area under the *CDF* for *TP* is the least for both farmers' practice *(FP)* and recommended practice *(RP)* at 1126 GH₵ and 1479 GH₵, respectively (Table 2). When ranking in order of *SSD*, $TP < PD < DP$.

5.4. Discussion

The results of this study demonstrate a general increase in crop yield and variability from farmers' practice *(FP)* to recommended *(RP)*. However, the increase in variability (i.e. yield and *GM*) is minimised when climate smart technologies *(CSTs)* are applied mainly for changing planting date (*PD),* making *PD* stochastically dominant over *Base* and other climate smart technology *(CST)* scenarios for maize and sorghum. This supports the concept that climate smart technologies can enhance climate risk resilience and minimise the adverse effect of climatic variability.

As *FP* and *RP* were modelled under different fertiliser application rates, the coefficient of variation which is a unitless measure of variability was employed instead of variance or standard deviation to compare variability across practices on an equal scale. The reduction in maize yield variability as measured by the coefficient of variation from *Base* to *PD* was 71.4% and 75% under *FP* and *RP* respectively whereas that of sorghum yield variability was 20% and 52.2% under *FP* and *RP* respectively. Reasons contributing to the less percentage reduction in sorghum yield variability relative to maize when *CSTs* are applied could be attributed to the drought-tolerant nature of the crop (Ahmad Yahaya et al., 2023). In addition, sorghum has been identified to often thrive under changing climatic conditions and can tolerate heat (Chadalavada et al., 2021). This suggests that the crop is less sensitive to water stress, making *CSTs* have little impact on yield variability reduction. Further, water is not a limiting factor for rice as it is grown close to the peak of the rainy season. Therefore, the impact of *CSTs* on reducing yield variability is marginal.

The results of this study also reveal the cost of *CSTs* significantly having an effect on the decision-making for risk-efficient *CSTs* among risk-averse farmers. Across all *CSTs,* mulching was the least preferred in terms of first order stochastic dominance and second order stochastic dominance. This is mainly due to the high cost of mulching, which eventually reduces gross margins. As most risk-averse farmers in the study area are relatively poor smallholder farmers, the ideal *CST* should be low-cost to attract adoption (Zakaria et al., 2020).

Table 2
Area under the cumulative distribution functions (*CDFs)* under farmers' practice (FP) and recommended practice (RP) for maize, rice, and sorghum in Ghana cedis (GH₵).

Scenarios[3]	Farmers' Practice (FP)			Recommended Practice (RP)		
	Area under the CDF's in GH₵					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	1000	305	–	2994	1609	–
M	1591	933	–	2909	1977	–
CB	1061	348	–	2346	1695	–
PD	913	263	1354	1686	1167	1938
DP	–	–	1434	–	–	1989
TP	–	–	1126	–	–	1479

[3]Base = No use of climate smart technology, M = Mulching, CB = Compartmental bunding, PD = Changing planting date, DP = Direct planting, TP = Transplanting.

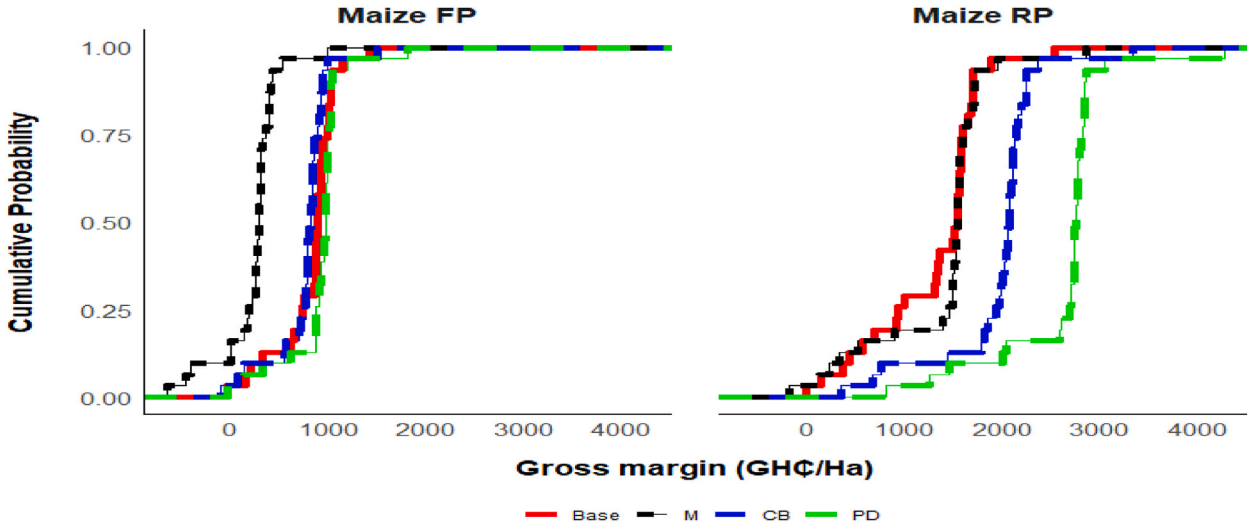

Fig. 5. Cumulative distribution functions (*CDFs*) for maize under farmers' practice *(FP)* and recommended practice *(RP)*.

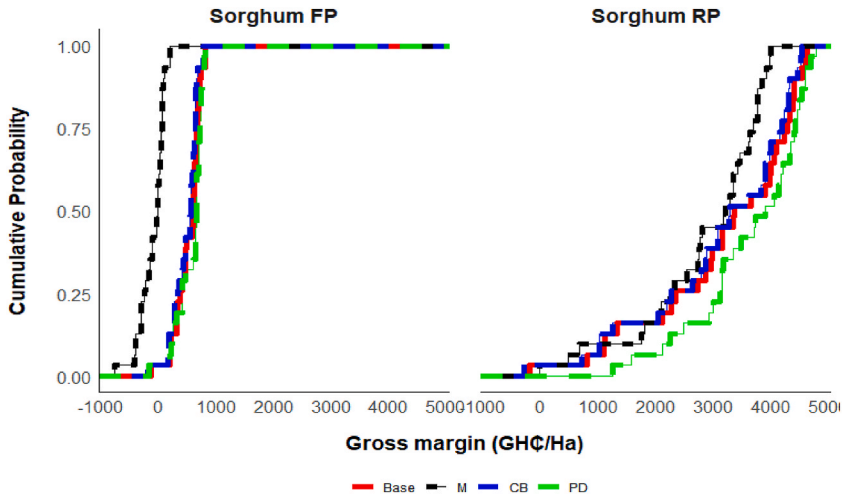

Fig. 6. Cumulative distribution functions *(CDFs)* for sorghum under farmers' practice *(FP)* and recommended practice *(RP)*.

Further, the results indicate that changing the planting date for maize and sorghum from April to May is risk efficient as against other climate smart scenarios primarily due to the relatively higher *GM*, yield, and the reduction in *GM* variability. In addition, transplanting rice appeared to be the most preferred option for the risk-averse smallholder farmers as yield and gross margin for transplanting increased under *FP* and *RP,* whereas changing planting date from June to July was less preferred. The lack of preference for rice planting in July for smallholder farmers could be explained by the fact that, the rainfall in the study area significantly drops after the September peak (Appendix 1). Also, under *FP* and *RP*, it is less risky for maize farmers to employ compartmental bunding and changing planting date as a climate risk resilient strategy compared to mulching. These results imply that *CST* recommendations should be driven primarily by cost, yield, and the gross margin variabilities associated with using them.

Furthermore, as highlighted by Anang et al. (2016), farmers face significant challenges in adopting recommended practices due to a lack of funding and limited access to credit facilities. This financial constraint makes it difficult for them to transition from low to recommended fertiliser application rates. Therefore, it is crucial to address the funding shortfall for the government's flagship initiative (the Planting for Food and Jobs policy) in Ghana (Donkor, 2024), to enhance farmers' access to fertilisers.

6. Conclusion

In this research, maize, rice, and sorghum crop yields for northern Ghana were simulated using soil type, crop parameters, and

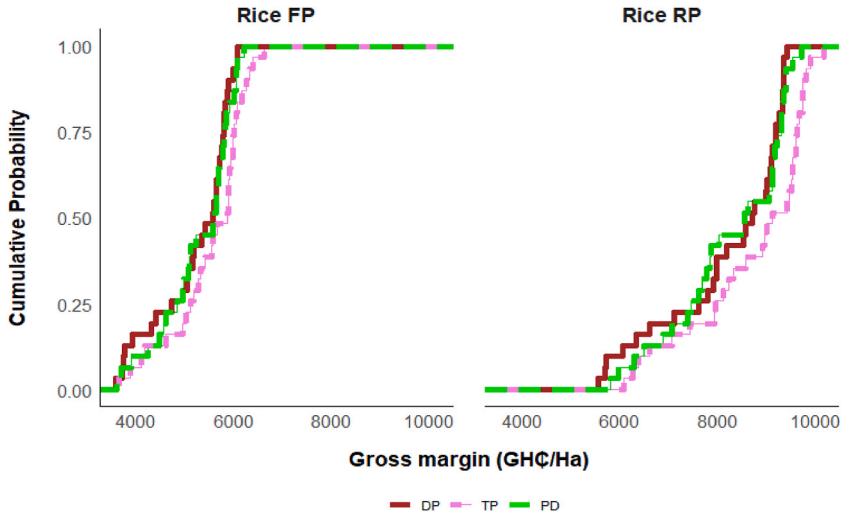

Fig. 7. Cumulative distribution functions (*CDFs*) for rice under farmers' practice *(FP)* and recommended practice *(RP)*.

climatic conditions to generate yield and gross margin outcomes for stochastic dominance analysis. As evident in literature, selecting risk-efficient climate smart technologies in northern Ghana from the perspective of smallholder farmers' risk aversion is a significant gap. The findings of this study have revealed the usefulness of low-cost and risk-efficient technologies such as changing planting dates, and transplanting as a crop-specific risk management guide for climate smart technology adoption policies under the assumption that smallholder farmers in the study area are risk averse.

From the outcome of this study, changing planting date from April to May for maize and sorghum farmers and transplanting rice were stochastically dominant over other climate smart technologies. This corroborates the findings in literature indicating an increase in yield when planting dates are changed to suit varying climatic conditions. Our study used crop modelling to select the ideal period for growing maize and sorghum in northern Ghana. Furthermore, to recommend a climate smart technology for smallholder farmers, transplanting was selected from our findings. Transplanting results in higher rice yield compared to broadcasting or direct planting. Transplanting at the recommended spacing rate results in higher yields as plants grow more vigorously and produce broader leaves that utilise sunshine for photosynthetic activities.

In brief, the information on *CST* alternatives analysed in this study can be helpful for climate smart intervention practitioners to identify technologies suitable for the smallholder farmer in the context of cost, when to plant, how to plant and the expected returns. Despite the usefulness of this research, the stochastic dominance approach provides no room to analyse the interaction effect among the *CSTs*, the heterogeneity of farm households, and other socio-economic conditions that may affect farmers decision making under risk. We recommend future research to focus on a sophisticated approach that captures the resource constraints of smallholder farmers, their heterogeneity in risk preferences, and optimal combination of technologies.

CRediT authorship contribution statement

David Ahiamadia: Conceptualisation, modelling, data collection and cleaning, analysis, and writing. **Thiagarajah Ramilan:** Review, Model validation, and editing. **Peter R. Tozer:** Review, Model Validation, and editing.

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.

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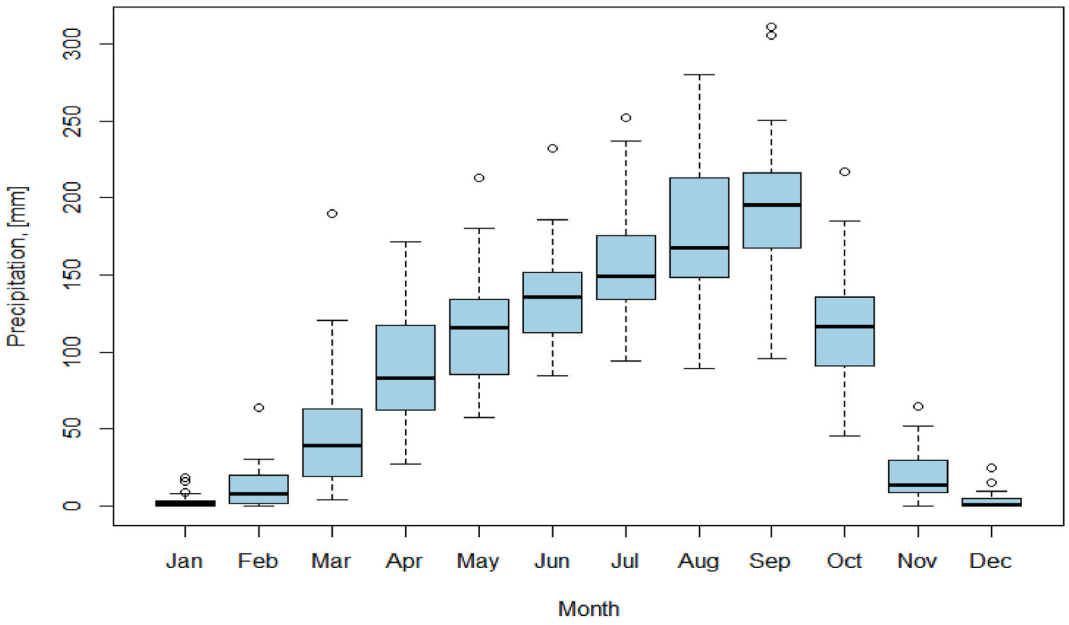
Appendix 1. Distributions of monthly precipitation for northern Ghana



Appendix 2. Crop parameters for maize

Crop Parameters	Value
Time from sowing to emergence (GDD-Growing Degree Days)	132
Time to maximum canopy cover (GDD)	1352
Time from sowing to maximum rooting depth (GDD)	1195
Time from sowing to start of canopy senescence (GDD)	1653
Time from sowing to maturity (GDD)	2175
Time from sowing to flowering (GDD)	1230
Duration of flowering (GDD)	532
Maximum effective rooting depth (metre)	1.0
Minimum effective rooting depth (metre)	0.30
Reference harvest index (%-Percentage)	40
Building up of Harvest Index (GDD)	872
Cultivar (Oba super 2)	–
Plant population (Plants/Ha-Plants/hectare)	53,333
Sowing date (Date)	Varies from year to year
Nitrogen fertilizer application rate (kgN/ha-Kilograms of nitrogen/hectare)	30 and 60
Soil fertility stress (%)	70

Appendix 3. Crop parameters for sorghum

Crop Parameters	Value
Time from sowing to emergence (GDD-Growing Degree Days)	248
Maximum canopy cover (%-Percentage)	70
Time from sowing to maximum rooting depth (GDD)	1797
Time from sowing to start of canopy senescence (GDD)	1709
Time from sowing to maturity (GDD)	1904
Time from sowing to flowering (GDD)	1230
Duration of flowering (GDD)	369
Maximum effective rooting depth (metre)	1.80
Reference harvest index (%)	45
Length building up of Harvest Index (GDD)	674
Normalized water productivity (gram/m^2 -grams per square metre)	33.7

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Crop Parameters	Value
Minimum air temperature range (^{o}C-Degrees Celsius)	+5 to +10
Maximum air temperature range (^{o}C)	+40 to +45
Shape factor for water stress coefficient for stomatal control	3
Plant population (Plants/Ha-Plants/hectare)	74000
Sowing date (date)	Varies from year to year
Nitrogen fertilizer application rate (kgN/ha-Kilograms of nitrogen/hectare)	0 and 80
Soil fertility stress (%)	70

Appendix 4. Crop parameters for rice

Crop Parameters	Value
Base temperature (^{o}C-Degrees Celsius)	8.0
Upper temperature (^{o}C)	30.0
Canopy size for transplanted seedling (cm^2/plant-Centimetre squared per plant)	5.5
Time from TP to recovery (GDD-Growing Degree Days)	92
Maximum canopy cover (almost entirely covered) (%-Percentage)	95
Time from TP to maximum rooting depth (GDD)	302
Time from TP to start of canopy senescence (GDD)	1376
Time from TP to maturity (GDD)	1992
Time from TP to flowering (GDD)	1292
Duration of flowering (GDD)	227
Maximum effective rooting depth (metre)	0.60
Minimum effective rooting depth (metre)	0.30
Reference harvest index (%)	55
Building up of Harvest Index (GDD)	654
Normalized water productivity (gram/m^2 -grams per square metre)	19
Minimum air temperature below which pollination starts to fail (^{o}C)	8
Maximum air temperature above which pollination starts to fail (^{o}C)	35
Minimum growing degrees required for full biomass production (^{o}C)	10
Shape factor for water stress co-efficient for stomatal control	3
Shape factor for water stress co-efficient for canopy senescence-upper threshold	3
Plant population for DP and TP (Plants/Ha- Plants per hectare)	250000
Sowing date (Date)	Varies from year to year
Soil fertility stress (%)	70

Source: Adbul-Ganiyu et al. (2018)

Appendix 5. Budget and labour requirement for Maize

Cost of items and activities	Maize budget					
	Farmer practice			Recommended Practice		
	Quantity/ Ha	Unit cost (GH₵	Total cost (GH₵)	Quantity/ Ha	Unit cost (GH₵)	Total cost (GH₵)
Land preparation	1	250	250	1	250	250
Seeds (kg)/Ha	18.8	1.9	36	22.5	1.9	43
Fertiliser (kg)/Ha	200	0.73	146	400	0.73	292
Herbicides (L/Ha)	5.1	6.3	32	5.1	6.3	32
Pesticides (L/Ha)	0.2	6.7	1.34	0.2	6.7	1.34
Transportation	–	–	101	–	–	151
Processing	–	–	73	–	–	109
Labour without CST*(person-days)	66.8	8	534	99.8	8	799
Total cost/Ha without CST			**1173**			**1677**
Cost of mulch	1	578	578	1	578	578
Mulching (labour in person days)	6	8	48	6	8	48
Compartmental bunding (Labour in person days)	10.5	8	84	10.5	8	84
Total cost/Ha with CST			**1883**			**2387**

Author's own construct based on extrapolation from Wongnaa et al. (2019)

* Labour without CST implies total labour in person days required for sowing, fertiliser application, pesticide application, harvesting, threshing, transportation and bagging.

Appendix 6. Budget and labour requirement for Sorghum

Cost of items and activities	Sorghum budget					
	Farmer practice (FP)			Recommended Practice (RP)		
	Quantity/ Ha	Unit cost (GH₵	Total cost (GH₵)	Quantity/ Ha	Unit cost (GH₵)	Total cost (GH₵)
Land preparation	1	250	250	1	250	250
Seeds (kg)/Ha	7.41	7.2	53	10	7.2	
Fertiliser (kg)/Ha	0	0	0	533	0.73	
Herbicides (L/Ha)	1	30	30	1	30	30
Pesticides (L/Ha)	1	30	30	1	30	30
Transportation (GHC)	–	–	101	–	–	151
Labour without CST*(person-days)	68.6	8	549	157	8	1256
Total cost/Ha without CST			**1013**			**1717**
Cost of mulch	1	578	578	1	578	578
Mulching (labour in person days)	6	8	48	6	8	48
Compartmental bunding (Labour in person days)	10.5	8	84	10.5	8	84
Total cost/Ha with CST			**1723**			**2427**

Source: Author's own construct based on extrapolation from Akuriba et al. (2011).

* Labour without CST implies total labour in person days for sowing, fertiliser application, weeding, harvesting, threshing, and bagging as indicated in Akuriba and Brempong (2011).

Appendix 7. Budget and labour requirement for rice

Cost of items and activities	Rice budget/Ha					
	Farmer practice (FP)			Recommended Practice (RP)		
	Quantity/Ha	Unit cost (GH₵)	Total cost (GH₵)	Quantity/Ha	Unit cost (GH₵)	Total cost (GH₵)
Land preparation	1	339	339	1	339	339
Seeds (kg)/Ha	21.3	6	128	23.1	6	138
Fertiliser (kg)/Ha	–	–	499	–	–	1069
Pesticides (L/Ha)	1	30	30	1	30	30
Direct planting (person-days/Ha)	12.9	8	103	14	8	112
Labour without CST*	59.4	8	475	101.9	8	815
Total cost/Ha without CST			**1574**			**2503**
Transplanting (person-days)	21	8	168	23.8	8	190
Total cost/Ha with CST			**1742**			**2693**

* Labour without CST implies total labour in person days for fertiliser application, weeding, pest and disease control, harvesting, threshing, transporting, and drying as indicated in Jakada and Ifyalem (2023).

Source: Authors own construct based on extrapolations from Akolgo (2021) and Jakada and Ifyalem (2023).

Appendix 8. Average yield(tons/Ha) total revenue (TR)/Ha, total cost (TC)/Ha, and gross margin (GM)/Ha, under farmers' practice and recommended practice for maize, sorghum and rice

Scenarios[4]	Maize- Average TR/Ha, TC/Ha, and GM/Ha							
	Farmer Practice (FP)				Recommended Practice (RP)			
	Yield (tons/Ha)	TR*/Ha (GH₵)	TC/Ha (GH₵)	GM/Ha (GH₵)	Yield (tons/Ha)	TR/Ha (GH₵)	TC/Ha (GH₵)	GM/Ha (GH₵)
Base	1.88	1986	1173	813	2.81	2955	1677	1278
M	1.91	2022	1799	223	3.47	3661	2303	1358
CB	1.89	2012	1257	755	3.5	3696	1761	1935
PD	1.96	2075	1173	902	3.57	3778	1173	2605
DP	–	–	–	–	–	–	–	–
TP	–	–	–	–	–	–	–	–
	Sorghum-Average TR/Ha, TC/Ha, and GM/Ha							
	Yield (tons/Ha)	TR/Ha-(GH₵)	TC/Ha-(GH₵)	GM/Ha (GH₵)	Yield (tons/Ha)	TR/Ha-(GH₵)	TC/Ha-(GH₵)	GM/Ha-(GH₵)
Base	0.81	1534	1013	521	2.61	4908	1717	3191
M	0.82	1540	1639	−99	2.76	5188	2343	2845
CB	0.82	1540	1061	479	2.61	4909	1801	3108

(continued on next page)

(*continued*)

Scenarios[4]	Maize- Average TR/Ha, TC/Ha, and GM/Ha							
	Farmer Practice (FP)				Recommended Practice (RP)			
	Yield (tons/Ha)	TR*/Ha (GH₵)	TC/Ha (GH₵)	GM/Ha (GH₵)	Yield (tons/Ha)	TR/Ha (GH₵)	TC/Ha (GH₵)	GM/Ha (GH₵)
PD	0.83	1572	1013	559	2.83	5352	1717	3635
DP	–	–	–	–	–	–	–	–
TP	–	–	–	–	–	–	–	–
	Rice- Average TR/Ha, TC/Ha, and GM/Ha							
	Yield (tons/Ha)	TR/Ha-(GH₵)	TC/Ha-(GH₵)	GM/Ha (GH₵)	Yield (tons/Ha)	TR/Ha-(GH₵)	TC/Ha-(GH₵)	GM/Ha-(GH₵)
Base	–	–	–	–	–	–	–	–
M	–	–	–	–	–	–	–	–
CB	–	–	–	–	–	–	–	–
PD	3.07	6835	1574	5261	4.83	10,762	2503	8259
DP	3.03	6761	1574	5187	4.79	10,701	2503	8198
TP	3.21	7144	1639	5505	5.06	11,291	2581	8710

[4] Base = No use of climate smart technology, M = Mulching, CB = Compartmental bunding, PD = Changing planting date, DP = Direct planting, TP = Transplanting.

[*] *TR = Total revenue for each crop is the product of the average yield and average price/ton for maize (i.e.,* GH₵ *1061), sorghum (i.e.,* GH₵ *1884), and rice (i.e.,* GH₵ *2233).*

Appendix 9. Average yield, gross margin, and coefficient of variation under farmers' practice and recommended practice for maize, rice, and sorghum

Scenarios[4]	Farmers' Practice (FP)			Recommended Practice (RP)		
	Yield coefficient of variation					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	0.07	0.05	–	0.12	0.23	–
M	0.04	0.04	–	0.08	0.16	–
CB	0.04	0.04	–	0.03	0.23	–
PD	0.02	0.04	0.05	0.03	0.11	0.06
DP			0.05	–	–	0.05
TP			0.04	–	–	0.03
	Gross margin coefficient of variation					
	Maize	**Sorghum**	**Rice**	**Maize**	**Sorghum**	**Rice**
Base	0.37	0.47	–	0.43	0.40	–
M	1.34	−2.15	–	0.44	0.37	–
CB	0.39	0.44	–	0.28	0.42	–
PD	0.35	0.41	0.13	0.23	0.26	0.14
DP	–	–	0.15	–	–	0.15
TP	–	–	0.13	–	–	0.14

[4] Base = No use of climate smart technology, M = Mulching, CB = Compartmental bunding, PD = Changing planting date, DP = Direct planting, TP = Transplanting.

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