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Climate variability, consumption risk and poverty in semi-arid Northern Ghana: Adaptation options for poor farm households

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ABSTRACT

This paper presents a micro-level simulation study on possible impacts of farm level adaptation strategies using a spatial dynamic hydro-economic model called Mathematical Programming based Multi Agent System. The model was validated for the Northern semi-arid region of Ghana. The simulation results revealed that climate variability has substantial impacts on the poverty and food security status of farm households. Policy interventions like the provision of agricultural credit and expansion of irrigation access are found to be highly important in reducing the adverse effects of climate variability for the capital constrained and poor rainfed farm households. However, to achieve significant changes in food security, a mix of adaptation strategies in the form of credit and irrigation has to be provided simultaneously. We also found that farm level adaption through shifting planting date as well as adopting early maturing crop varieties can substantially reduce the adverse impacts of climate variability.

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1. Introduction

Sub-Saharan Africa (SSA) is considered to be the most vulnerable region to current and future climate variability (Conway and Schipper, 2011; Seipt et al., 2013). Particularly in Ghana, an increase in mean annual temperature of 1 °C per decade since 1960 and a decrease of monthly rainfall by about 2.4% per decade was recorded (De Pinto et al., 2012). Moreover, an increase in future mean annual temperature with erratic rainfall distributions is expected (De Pinto et al., 2012; Lodoun et al., 2013). Such shifts in rainfall distribution and changes in temperature might therefore have an adverse consequence on agriculture in general and on food security and poverty level of farm households in particular. While reducing poverty and ensuring food security is a major priority, the rise in climate variability along with dependencies on climate-sensitive agriculture is becoming a major problem in reducing poverty and food insecurity (Hertel et al., 2010; Seipt et al., 2013). In many developing countries, climate variability is recognized to be the single most important factor responsible for large variations in food security and poverty among smallholder farmers (Dercon, 2004; Hertel et al., 2010). In this regard, Ghana's economy is highly exposed to the adverse effects of climate variability as agriculture forms the basis of the economy contributing roughly 30% to GDP and providing livelihood for 60% of the population (Sarpong and Anyidoho, 2012). The adverse effects are expected to be stronger since agriculture is predominantly rainfed with minimal irrigation coverage (Oloukoi et al., 2013).

It has been well documented that climate variability poses threats to food security through its adverse effect on crop productivity and consequent rise in commodity prices (Hertel et al., 2010; Wheeler and von Braun, 2013; Thornton et al., 2009; Briner et al., 2012; Bobojonov and Hassan, 2014; Seipt et al., 2013; Obeng et al., 2013). Moreover, climate variability also provides opportunities for farmers (net seller producers) through earnings from higher food price. The overall effect of climate variability on poverty and food security therefore depends on the magnitude of productivity shocks, the rate and speed of productivity induced market price changes, the market position of households (net buyer vs. net seller) and the extent of market integration of farm households. The empirical evidences so far however reveal that climate variability has adverse effects on food security (Wheeler and von Braun, 2013; Hertel et al., 2010; Claessens et al., 2012). Given that the direct effects of climate variability are transmitted through the agricultural sector, improving its capacity to adapt to the adverse effects of climate related shocks is considered as top priority for many developing countries in SSA including Ghana (Di Falco and Bulte, 2013; Oloukoi et al., 2013). However, there are very few empirical studies which explore the effectiveness and impacts of farm level adaptation measures in the context of small-scale and semi-subsistence agriculture. In addition, recent policy debates on climate variability have been focusing on the impact of climate variability rather than on the role of adaptation(Di Falco et al., 2011; Schilling et al., 2012; Obeng et al., 2013).

Even though, climate variability threatens decades of improvement towards improving poverty and food security in many developing countries (Wheeler and von Braun, 2013), there is some evidence to suggest that adaptation is occurring in response to climate variability. Farm households in Ghana for example, have undertaken a mix of different adaptation strategies such as planting new crop varieties, changing planting dates, growing drought resistance crops, use of crop insurance mechanisms, irrigation, use of short term production credit and adoption of soil and water conservation practices(De Pinto et al., 2012; Obeng et al., 2013). However, like many developing countries, farm households in Ghana suffer from an adaptation deficit which makes them vulnerable to climate variability(Milman and Arsano, 2013).This is particularly worrying since the presence of adaptive capacity is a necessary condition for designing effective adaptation strategies (Brooks et al., 2005). Reducing the adverse effects of climate variability therefore requires overcoming the existing climate variability deficits and responding to future climate variability through adaptation and policy interventions (Milman and Arsano, 2013).

In this paper, we seek to contribute to the climate change literature by quantifying the role of adaptation strategies at household level. More specifically, we examined whether adaptation strategies in response to climate variability are effective in improving poverty and food security levels of farm households. We identified four well known practices, typically adopted by farmers to reduce their exposure to the effects of climate variability based on studies by Nedumaran and Berger (2009), Obeng et al. (2013) and Yilma (2005). These are changing planting date, growing early mature varieties, use of irrigation and short-term production credit. The reminder of the paper is organized as follows: Section 2 briefly introduces the study area along with the data source and methods applied. In addition, this section presentes model validation results; Section 3 discusses our findings and their relevance for climate impact assessments, and Section 4 concludes with a list of open questions and an outlook on next research steps.

2. Material and methods

2.1. Description of study area

The study area is located in the Upper East Region (UER) of Ghana, which is the poorest among the 10 regions in Ghana (Gyasi et al., 2006). The poverty level in UER (70%) is much higher than the national poverty level of Ghana (28%). The UER is relatively densely populated; 104 person per km^2 as compared to the national average of 75 person per km^2 (GSS, 2004). The study area is characterized by an unfavorable biophysical environment with frequent failure and uneven distribution of rainfall, rather poor soil quality and often land degradation (Yilma et al., 2008). Besides these adverse biophysical conditions, factors like lack of access to credit and insurance markets, high costs of inputs, and poor infrastructure are very prevalent (Yilma et al., 2008). The study area encompasses the Vea and Tono irrigation schemes and various small reservoirs within a sub-basin of the White Volta River. The farm households in this area are mainly subsistence farmers and grow rainfed crops in the rainy season (April to September) and irrigated crops in the dry season (November to March). The main food crops are rice, millets, groundnut, maize and beans. Cash crops grown in the study area include tomato, onion and leafy vegetables. The main livestock types kept in the study area include cattle and small ruminants such as goats and sheep.

2.2. Data source and methods

The data used in this study comes from the household survey conducted as part of CGIAR challenge program on water and food and from the 1998/99 Ghana Living Standard Survey (GLSSIV). Building on the above two data sets, a multi-period non-separable hydro-economic model called Mathematical Programming Based Multi-Agent System (MPMAS) is developed to examine adaptation options of smallholder farmers in Ghana. MPMAS[1] incorporates extensive module components such as socio-economic decision module, communication network module, consumption module and crop growth module for climate impact analysis (Berger, 2001; Schreinemachers et al., 2007; Schreinemachers and Berger, 2011). Household decision making is modeled using mathematical programming (MP) techniques. The MP approach assumed each household to maximize the expected utility,which consists of cash income from sales (crop and livestock products) and off-farm labor, in-kind income from self-consumption of crop and livestock products, and the annuity of future expected income from investments) under constraints such as different types of land, labor, capital, irrigation water, consumption requirements, etc. Due to the presence of market imperfections in the UER, cash income and in-kind home consumption objectives are included separately in the model objective function, i.e. the production and consumption decisions of households are non-separable and must both be taken into account when optimizing land use decisions (Holden and Shiferaw, 2004; Woelcke, 2006; Schreinemachers and Berger, 2011; Nedumaran et al., 2014). The aggregate structure of household decision model is given in (Appendix B). For each year in the simulation, investment, production and consumption decisions of households are captured. The matrices are household-specific and differ in

[1] As described by Schreinemachers and Berger (2011), MPMAS captures agent to agent interaction and agent to environment interactions. Agent to environmental interactions are captured through climate variability effects on agricultural productivity while agent to agent interactions include information sharing about new technologies, as well as the bilateral exchange of scarce resources (e.g. water and land) and certain forms of collective action (e.g. irrigation water use). In particular we modeled agent to agent interactions in technology diffusion by using a frequency-dependent contagion effect; the more agents adopt a technology, the more it becomes accessible to others.

terms of internal matrix coefficients (e.g., yields and consumption function coefficients), objective function (e.g., prices) and resource constraints (e.g., resource endowments, assets and liquid means).

The crop specific effect of climate variability on yield is captured through the crop growth model component of MPMAS based on the FAO 56 approach (Clarke et al., 1998; Smith, 1992). The model is parameterized through daily precipitation and temperature data. The crop-water requirement (CWR) for crop i in month m is the product of a crop coefficient (Kc), the potential evapotranspiration ($ET0$), and the planted area (A)

$$CWR_{i,m} = Kc_{i,m} ET0_m A_{i,m} \tag{1}$$

The CWR is met through rainfall and complemented via irrigation (IRR). In the model total rainfall is converted into effective rainfall (ERF) using the USDA soil conservation service formula to capture the share of rainfall actually available to the crop, depending on its growth stage. Deficit irrigation water (DIRR) was then calculated as the difference between the crop water requirements and the effective water supply which include effective rainfall and irrigation:

$$DIRR_{i,m} = CWR_{i,m} - ERF_{i,m} - IRR_{i,m} \tag{2}$$

The crop yield reduction factor (CYF) which captures the effects of climate variability on crop yield for each crop is then computed as:

$$CYF_c = 1 - Ky_c\left(1 - \frac{ETA_c}{ETC_c}\right) \tag{3}$$

Where Ky_c captures the yield response factor of each crop[2] , ETA_c captures crop specific actual evapotranspiration and ETC refers to the potential crop evapotranspiration values. The model effectively, captures the effects of extreme dry and wet conditions. In the extreme drought case as well as extreme wet conditions, crop yields will be zero (Block et al., 2008). Moreover, CYF value less than 0.5 lead to crop failure under normal condition (Berger, 2001; Block et al., 2008). The main source of irrigation water in the Upper East Region is surface water and rainfall which were simulated with the distributed hydrology model WASIM-ETH. The two large-scale irrigation projects (Tono and Vea), 88 small dams and river water pumping at the White Volta River are the source of surface water supply. The available irrigation water in each irrigation site (inflow) is then shared among the model agents based on their amounts of irrigable land in that particular irrigation site.

To capture the consumption and poverty level in the UER, the consumption part in the model included a detailed budgeting system that allocates the income from farm and non-farm activities to savings, food and non-food expenditure and into different types of food items. In the first stage, the model captures the standard economic relationship between savings and income.

$$Y = S + TE \tag{4}$$

Where Y refers to total household income, S refers to saving and TE captures total expenditure. For a given household, savings is specified as a function of income and other household specific characteristics affecting savings levels.

$$S = \alpha_0 + \beta_1 Y + \beta_2 Y^2 + \beta_3 x^{hc} + \sum_{n=1}^{n} \beta_n D + \mu_i \tag{5}$$

Where S is total savings from a given level of income, Y is the total disposable income, x^{hc} includes household characteristics such as sex and age and D is a vector of regional dummies.[3]

The second stage, where households allocate expenditure between food and non-food items, is captured using a modified version of the Working-Leser model, following Schreinemachers et al. (2007). In this decision, agents allocate income after-savings into food and non-food expenditures.

[2] These values are predefined for each crop-stage and for the season as a whole, and can be found in FAO Publication 33. K_y values below 1 indicate resistance to drought while values above 1 point to ward drought sensitivity (Block et al., 2008).

[3] regional dummies capture regional fixed effects(differences in saving and consumption behavior etc).

For this study, the modified version of the Working-Leser model is specified as follows:

$$S = \alpha_0 + \beta_1 Y + \beta_2 Y^2 + \beta_3 x^{hc} + \sum_{n=1}^{n} \beta_n D + \mu_i \tag{6}$$

where ω_i is the share of food expenditure from the total expenditure, *PCE* is per capita expenditure, x^{hc} are household and demographic variables and *D* is a vector of regional dummies. In the final stage, where agents allocate food expenditure to specific food items is parameterized using the linear version of the AIDS model (Deaton and Muellbauer, 1980). In all of the specifications, the budget share equation for each food category is specified as a function of its own price, the price of other goods in the demands system and the real total expenditure on the group of food items. Specifically the model is presented as follows:

$$w_i = \alpha_i + \sum_{j=1}^{j} \gamma_{ij} lnp_j + \delta_i \left(\frac{x}{\sum_{n=1}^{n} w_n lnp_n} \right) + \varphi_i x^{hc} + \sum_{n=1}^{n} \beta_n D + \mu_i \tag{7}$$

where w_i refers to the budget share of food category *i*, *p* is a vector of prices, *x* refers to the total per-capita food expenditure, x^{hc} is a vector of household characteristics and *D* is a set of regional dummies. The complete demand system for LA/AIDS was then estimated using Zellner's Seemingly Unrelated Regression (SUR) technique, imposing the additional constraints of homogeneity, adding-up, and symmetry.

2.3. Model validation

According to McCarl and Apland (1986), model validation is an important part of empirical economic analysis. Simulation results should therefore be cross checked through association tests between simulated results and real world observed values. Similarly, Marks (2007) pointed out that hydro-economic models need to be validated at micro and macro level to make sure that the model realistically replicates the reality. In this study, the model was validated by conducting regression analyses between observed and simulated land use values from running the baseline scenario. The baseline reflects the current situation and assumes the current trend in demography, diffusion of innovations, prices and rainfall. A regression line was fitted through the origin for the observed and predicted land use of main seven crops expressed in percentage to total area of these crops. A perfectly validated model would be indicated by a slope coefficient of one and an R^2 of one (McCarl and Apland, 1986). The parameter coefficient of 0.96 and R^2 of 0.98 indicates that the model results are identical with the current trend (Table 1).

Table 1
Model validation results.

Level	Slope Coef	Std.error	R^2
Micro(clusters)[a]	0.99	0.08	0.96
cluster 0	0.98	0.05	0.98
cluster 1	1.06	0.17	0.93
cluster 2	0.95	0.05	0.98
cluster 3	0.94	0.06	0.96
Macro(catchment)	0.96	0.01	0.98

[a] Clustering is made based on homogenous characteristics of agents(households).i.e. households with the same behavior with respect to a very important variable such as land size are classified within one cluster. Therefore household behavior with respect to a certain variable is extrapolated in the cluster and usually households of similar behavior are grouped in the same cluster.

3. Results and discussions

In this section, we present the simulation results carried out to examine possible adaptation options in the context of poor farm households in Northern Ghana. The simulation results were divided in four sections: (i) baseline with climate variability, (ii) adaptation through credit access, (iii) adaptation through irrigation, and (iv) The effects of intra-rainfall distribution and adaptation mechanisms through changing planting dates and adopting early maturing crop varieties.

3.1. Baseline

To capture the effects of climate variability, we first compute the Standardized Precipitation Index (SPI) coefficient to classify the state of weather condition into wet, normal and dry years. For each weather realizations, we then simulated the distribution of production and poverty. The normal rainfall scenario is used as a reference to compare production and poverty changes due to climate variability. The production and poverty distribution under each rainfall scenarios is presented in Table 2. The result shows a substantial reduction in total production[4] under dry rainfall conditions compared to the normal rainfall condition. Based on the official poverty line of Ghana,[5] the proportion of households living under the poverty line has increased by 12% in dry rainfall years compared to normal rainfall condition. Not only the head count ratio but also the severity of poverty as measured by squared poverty gap ratio has increased by 15% which implies that the effects of climate variability are more pronounced on the poor. The results are in line with the findings by Gyasi et al. (2006) and Nedumaran and Berger (2009) who reported a poverty incidence level of 70% for normal years in Northern Ghana.

Table 2
Effects of climate variability on production and poverty level.

Category	Normal	Wet	Dry
Changes in total production (%)	–	12	−38
Headcount ratio (%)	73	69	81
Poverty gap ratio (%)	38	36	54
Squared poverty gap ratio (%)	23	20	38

Note: Average value over 15 years of simulation.

The result[6] further shows that climate variability induced productivity changes in labor and land are instrumental for the changes in poverty. In particular, average land and labor productivity declined by 38% and 40% respectively during dry rainfall years compared to the normal rainfall years. Likewise, the marginal productivity of land and labor became negative during dry rainfall year and were diminishing at best during wet rainfall years. Policy interventions which enhance labor productivity could therefore be helpful in improving productivity in order to enhance food security in normal rainfall years (Table 3).

3.2. Role of short term credit

Studies by Milman and Arsano (2013) showed that households tend to adapt to climate variability effects through a wide range of *ex-ante* and *ex-post* measures. In addition, not all adaptation options

[4] Total production is computed from changes in the yield level of major staple crops (mainly rice, millet, bean, groundnuts and maize).

[5] The official poverty line for the study region is fixed at a welfare level of a person who meets 2,300 kcal per day per adult equivalent. The SI conversion factor of one kilocalorie is 4.184 J. Expressing the average annual energy requirement of an adult male (18–62 years old) in Ghana results in a poverty line of 3.259 GJ per capita and year

[6] Results presented in the tables are averages of 15 years. Moreover, households with energy consumption level of below 2300 kcal per day are considered to be poor.

Table 3
Productivity of key inputs under climate variability.

Scenario	Wet	Dry
Marginal productivity of labor	0.05	−0.44
Average productivity of labor	2.94	1.73
Marginal productivity of land	843	630
Average productivity of land	2505	1540
Marginal productivity of water	0.035	5.65

are equally important and effective since households differ in terms of income, resource endowments and adaptation capacity. In the following section, we examined the potential roles of short-term production credit as a mechanism to adapt the adverse effects of climate variability.

It has been well documented that poor agricultural households in many developing countries lack adequate access to credit in order to invest enough to get productivity gains in light of climate variability (Suri, 2011; Ellis, 2000). Moreover, past studies on the role of microfinance have shown that the provision of credit is crucial in enhancing adaptation to climate variability (Ellis, 2000; Di Falco and Chavas, 2009). However, very little is currently known about to what extent the poor are benefited from credit especially from an adaptation perspective (Di Falco et al., 2011).

In the case of Ghana, different pro-poor policies have been implemented to reduce climate variability induced exacerbates in poverty. At the forefront of these policy interventions is the provision of short term production credit with the premise that it could reduce poverty both in the short run and long run by relaxing the capital constraints of many smallholder farmers. While examining the impacts of credit, we first analyzed whether such policy intervention is a pro-poor policy instrument by estimating the kernel density distributions of poverty under the normal rainfall conditions (Fig. 1). Our result reveals that access to credit is an important policy instrument to reduce poverty substantially, as most of the poor households crossed the poverty line. Moreover, the poorest agents would substantially benefit from access to credit, as the tail of the distribution has shifted to the right.

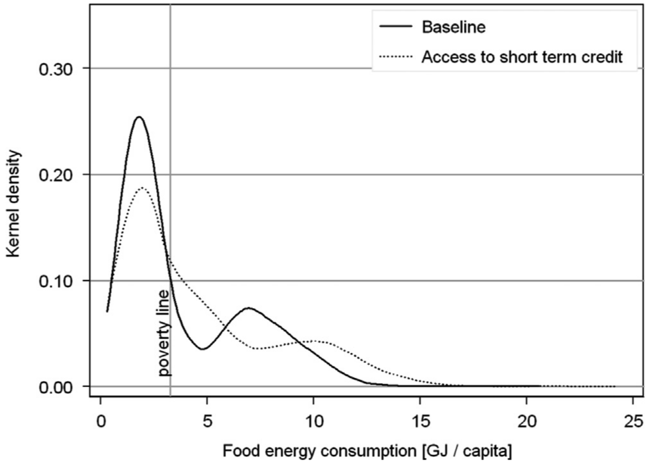

Fig. 1. Effectiveness of credit.

Next, we examine the role of credit as adaptation mechanism by comparing simulation results with and without credit under different rainfall trajectories. Our first result imply that with the provision of agricultural credit, poverty level can be substantially reduced as households were able to change their land use from subsistence rainfed farming to high value crop irrigation farming. Even

Table 4
Poverty trends with agricultural credit provision.

Scenario	Headcount ratio (%)	Poverty gap ratio (%)	Squared poverty gap ratio (%)
Wet years			
Baseline	69	36	20
Credit	42	21	12
Dry years			
Baseline	81	54	37
Credit	61	38	25

Note: Average value over 15 years of simulation.

with 25%[7] of interest rate, the model suggests that households demand credit and expand their area under irrigation. Moreover, we observed that the application of mineral fertilizer (in kg per ha) could also triple with access to credit which would help to improve the sustainability of agricultural land use in the region. The results further underline the need to rethink the current policy focus in Northern Ghana: more instruments should be tested for provision of credit and increased public investment in order to improve the physical access of irrigation land for poor farm households, which might bring the intended results of poverty reduction as well as diversification of agricultural production in the region (Table 4).

3.3. Role of irrigation

From our previous results, we have shown that the distribution of poverty very much depends on the nature of rainfall distribution. In this section, we concentrate on the potential role of irrigation since it has been reported in a considerable number of empirical studies from developing countries as a major adaptation mechanism against climate variability (Deressa et al., 2007; Nedumaran and Berger, 2009). We classified farm households in to two: the first group consists of only rainfed farmers and the second group consist farmers with irrigation access.[8] Our simulation result shows a marked difference in terms of income between households with and without access to irrigation. It can be argued that since farmers with irrigation access can produce at least twice per year, the income level should not be considered as a bench mark for comparison. We document this in our study since in the normal years; the average income of farm households with irrigation access is 48% higher than rainfed farmers. However, we also found that farmers with irrigation access are still vulnerable to the effects of climate variability, since a significant portion of their income is obtained from rainfed production. For example, in dry years, per capita food energy consumption declined by 43% and 37% for rainfed and irrigated farmers respectively. This result underscores the fact that farmers without irrigation access will suffer substantially following unfavorable rainfall distributions compared to farmers with irrigation access.

The other interesting result from our simulation analysis on the potential role of irrigation as a major adaptation strategy is that, irrigation without credit access cannot substantially reduce the adversity of climate variability. With credit and irrigation access, poverty head count rate declined by 43% during dry rainfall years compared to the situation of no credit and irrigation access (Table 5). The simulation result on the role of credit and irrigation confirmed a synergetic relationship in using credit and irrigation as an adaptation measure. Credit and irrigation can be used as an adaptation measure separately however with little impacts on poverty. If significant changes are to be achieved, a mix of adaptation strategies in the form of credit and irrigation has to be provided simultaneously.

[7] Provision of credit opportunities at 25% interest rate was identified as a potential entry point based on expert opinions in the CPWF project as well as studies by Nedumaran and Berger (2009) and Yilma (2005.

[8] Note that farmers with irrigation access do not practice a year round production with irrigation. Instead, they grow rainfed crops in the rainy season and complement production with irrigation during the dry season. Moreover, even for farm households with irrigation access, significant proportion of their production is done under rainfed due to liquidity constraints.

Table 5
Effectiveness of Irrigation as an adaptation option.

Variables	Scenario	Wet years		Dry years	
		Rainfed	Irrigation	Rainfed	Irrigation
Mean Income (Cedi)	Baseline	915	1794	557	1073
	Credit	1240	2655	701	1969
Crop Income (Cedi)	Baseline	692	1534	327	811
	Credit	1087	2439	506	1774
Per-capita-food energy consumption(GJ/capita)	Baseline	2.8	4.9	1.66	3.02
	Credit	3.6	6.4	2.11	5.1
Head count ratio (%)	Baseline	79	55	88	71
	Credit	50	16	73	28
Poverty gap ratio (%)	Baseline	41	30	59	48
	Credit	26	7	45	13
Squired poverty gap ratio (%)	Baseline	23	17	40	34
	Credit	14	4	30	8

Note: Average value over 15 years of simulation.

This finding shades some lights into the current policy debates on adaptation strategies. It should also be stressed that the failure of many adaption mechanisms is linked to the lack of integrated approach. While providing credit or irrigation is potentially important, it is not as effective as providing simultaneous credit and irrigation access. This is particularly an important policy recommendation for many policy makers in many developing countries as farmers face liquidity constraints to make the necessary investments in irrigation to boost production.

3.4. Intra-rainfall distribution and adaptation mechanisms

So far the analysis of poverty was mainly based on the total amount of rainfall and it does not consider irregular distribution of rainfall in critical months such as during the planting or harvesting stage of crops which is a prominent feature of rainfall in the study area. To take into account irregular distribution of rainfall, a scenario for shortage of rainfall during the planting, harvesting stage and throughout the whole growing period is considered. In northern Ghana, many crops are planted in the month of May due to the uni-modal nature of rainfall. Rainfall changes around May and April may therefore bring substantial problems for farmers and one way to cope with this problem is to shift planting period. In this section the impact of rainfall irregularities during planting and harvesting stage is presented and the next section will show how shifting planting date could help farmers cope the problem of rainfall irregularities at critical periods of the production season.

As shown in Table 6, poverty incidence level increases substantially when rainfall is very irregular at the onset. In the scenario where we considered reduction of rainfall during planting stage, we assumed rainfall to follow the normal trend except for April and May which was adjusted and assumed to follow the trends of March. With SPI classification the rainfall amount is normal and enough for any crop to grow if one considers the mere size of total rainfall. However, because of irregularities in rainfall during the planting stage, production is substantially reduced and hence poverty incidence level increased to 82%. This result shows the importance of capturing intra annual rainfall variabilities instead of yearly averages. We therefore argue that for agricultural production, it is more important to consider intra annual variabilities instead of yearly averages. Not only irregularities during planting stage, inadequate rainfall in the final growing stage of the crop is also important in determining the final production level. Our result shows that shortage of rainfall during harvesting stage leads to poverty incidence level of 81% (Table 6). In the extreme dry scenario, shortage of rainfall throughout the entire growing season is considered. This is done by reducing rainfall amount by 25% from the dry rainfall years. The result indicated that prevalence of extreme dry weather leads to poverty level of 88%.

The analysis undertaken in the previous section revealed that rainfall variability during the planting and harvesting stage could lead to a substantial loss of production and hence aggravates the

Table 6
Poverty under rainfall irregularities.

Scenario	Normal rainfall	Planting rainfall[a]	Harvesting rainfall[b]	Extreme dry scenario
Head count ratio (%)	73	82	81	88
Poverty gap ratio (%)	38	53	53	63
Squired poverty gap ratio (%)	23	35	36	47

Note: Average value over 15 years of simulation.

[a] This scenario refers to reduction of rainfall during the planting stage. In this scenario, we assumed that rainfall will follow the normal trend except for April and May which was adjusted and assumed to follow the trends of March.

[b] This scenario refers to reduction of rainfall during the harvesting stage. In this scenario, we assumed that rainfall will follow the normal trend except for the month of September and October. For September and October, rainfall was adjusted to follow the trends of March.

problem of poverty and food insecurity (Table 6). One way of coping rainfall irregularities during the planting stage is to shift planting date for rainfed crops. In Northern Ghana, farmers produce different types of rainfed crops with different levels of technology and input intensity. We therefore considered shifting planting dates only for crops with substantial shares in terms of production volume and area. These include staple crops mainly that of rice, millet, groundnut and bean. In the model, farmers are allowed to choose between postponing their planting date and continuing to plant crops as before. This scenario is important to assess the tendency of farmer's adaptation to climate variability. The decision of households to switch planting date alters input allocation across different crops and hence area share allocated for each crop. In addition, it leads to different production level and hence poverty incidence levels.

From the simulation experiment we observed that farmers in the study area could respond to climate variability through adaptation. The result also revealed that farmers do not completely shift planting date; instead they opt to allocate land for both activities. In the model however, it is assumed that agents can get timely meteorological information and input access. In this regard, providing up to date meteorological information about rainfall plays a very important role for farmers to implement changing planting date. Adjusting planting dates when rainfall is irregular particularly during planting stages leads to a substantial gain of productivity. In our simulation experiment, we found that productivity of millet, bean and groundnuts has increased by 45%, 25% and 82% respectively (Table 7). This shows that rainfall variability in the area could lead to substantial losses in production which is a very critical argument for food security. The significance of these productivity changes in enhancing food security is examined using the food poverty line. When farmers plant based on past experience-without considering the potential impact of rainfall shortage, 91% of farmers fall below the poverty line while the poverty incidence rate declines to 48% after shifting planting dates (assuming farmers have prior information on rainfall). This perhaps explains the importance of adaptation and coping mechanisms to reduce the impact of climate variability. This however calls for asset base intervention to make institutional set ups smooth and well-functioning to improve input availability. The model result showed that farmers will implement adaptation and coping mechanisms whenever they have the opportunity. This however is not always true as farmers may face economic and institutional constraints. Moreover, in the model it is assumed that households can get timely meteorological information and input access. In this regard providing up to date meteorological information about rainfall plays a very important role for farmers to implement shifting planting date.

Table 7
Effects of changing planting date.

Scenario	Before Shifting planting date	After shifting planting date	Change (%)
Millet yield(ton)	0.553	1.003	0.45
Bean yield(ton)	0.18	0.24	0.25
Groundnut yield(ton)	0.102	0.58	0.82
Head count ratio (%)	91	48	43

Note: average value over 15 years of simulation.

Next we discuss how introducing Short Growing Period (SGP) seeds improve production when rainfall is short in the late growth stage of crops. We implemented two SGP seed varieties for groundnuts and bean because of their relevance in the study area. The growing period of these particular crops is then reduced from 6–3 months. It is assumed that the price and per hectare seed requirements of the new crop will be the same as that of improved maize seed price and seed requirements.[9] Growing these varieties is introduced in a way that gives agents the possibility of either going for SGP varieties or continue to produce the previous LGP (Long Growing Periods) varieties. The cost of production for the newly introduced activities is higher than the LGP varieties by the cost of seed. Households will therefore face a tradeoff in growing crops with a lower production cost with high risk of lower production and growing plants with higher initial cost with less risk of reduced production. This is equivalent to the choice of forgoing future consumption for current benefits versus forgoing current benefits for future benefits. The result perhaps will show the risk tendencies and preferences of agents in addition to their decision making at times of climate variability. As shown from the table below the result is as expected and households make a lot of adjustments in order to produce crops with shorter growing seasons (Table 8).

Table 8
Effects of short growing period varieties.

Scenario	Crops considered	Yield(ton)	Change (%)
LGP	Bean	0.157	
	Ground nuts	0.051	
SGP	Bean	0.26	80
	Ground nuts	0.23	32

4. Conclusions and policy implications

As part of the Millennium Development Goal (MDG), poverty has been at the center of attention among policy makers in Ghana. Recently, the need to establish the likelihood impacts of climate variability has been emphasized as the link between poverty and climate variability has been far less established (Hertel et al., 2010). Understanding the causal relationship between climate variability and poverty is vital for designing appropriate policy intervention to mitigate the impact of climate variability as well as to explore adaptation possibilities. In this regard, we considered agriculture as the primary means through which the impacts of climate variability are transmitted to the poor since agricultural production under semi-arid conditions remains the main source of income for most rural communities in Northern Ghana.

Adaptation strategies, such as changing of planting dates, growing early maturing crop varieties, provision of short term agricultural credit and irrigation were implemented and the level and impact of adaptation was estimated. The simulation results revealed that climate variability has substantial impacts on the poverty and food security status of farm households. Policy interventions like the provision of agricultural credit and expanding irrigation access are found to be highly important in reducing the adverse effects of climate variability for the capital constrained and poor rainfed farm households. However, to achieve significant changes, a mix of adaptation strategies in the form of credit and irrigation has to be provided simultaneously. The analysis of farmer's adaptation to increasing climate variability suggest that farmers would implement adaptation measures such as

[9] Since there was no data about the price of new varieties for groundnut and bean, we assumed that it will be similar to the market price of improved maize in the study area. Since the correlation between duration of the crop and yield potential is very high. The yield potential of the short duration varieties are lower than the long duration

shifting planting dates, growing early maturing crop varieties and use of irrigation to reduce the anticipated adverse effects of climate variability.

In particular we suggest that in order to reduce poverty under increasing climate variability, policy interventions should focus on assisting poor households to accumulate assets through increased investment in irrigation and credit provision schemes. Moreover, since farm households vary significantly in their resource endowments and their response to policy and technological interventions, policy incentives need to account for differences across farm households while designing and implementing policy interventions. With increasing risk of climate variability and lack of agricultural credit, the use of income generated from off-farm labor market could also be important in enhancing food security. Promotion of off-farm employment opportunities as well as complementary trading options in addition to agricultural activities could be used as a way out to reduce the impact of climate variability.

Appendix A

See appendix Tables 1–8.

Appendix B. Aggregate structure of household decision model.

Constraint	Grow Rainfed crops	Grow Irrigated crops	Invest in new livestock	Maintain livestock	Sell crops	Sell Livestock	Consume own food	Purchase food	Hire in labor	Hire out labor
Objective Function					+C	C	C		−C	+C
Rainfed Land (ha)	+1									
Irrigated Land (ha)		+1								
Labor (man-days)	+A	+A	+A	+A					−1	+1
Water (liters/sec)		+A								
Livestock (head)			−1	+1		+1				
Cash (GH. Cedi)										
Variable inputs (Kg)	(+A)	(+A)								
Current Yield (Kg)	(−Y)	(−Y)	(−Y)	(−Y)	+1	+1	+1			
Future Yield (Kg)			(−Y)	(−Y)						
Income identity (GH. Cedi)							+C		−C	+C
Total Expenditures										
Food Expenditures										
Food Consumption							−C	−C		
Food energy Balance							−A	−A		
Food energy requirement (BJ)										

Constraint	Purchase inputs	Short-term credit	Deposit cash	Income transfer	Food expenditures	Food consumption	Food energy needs	Sell produce in future	Sign	RHS
Objective Function	−C	−C	C					C		MAX
Rainfed Land (ha)									≤	B
Irrigated Land (ha)									≤	B
Labor (man-days)									≤	B
Water (liters/sec)									≤	B
Livestock (head)									≤	B
Cash (GH. Cedi)	(+C)	−1	−1						≤	B
Variable inputs (Kg)	(−1)								≤	B
Current Yield (Kg)									≤	0
Future Yield (Kg)								+1	≤	0
Income identity (GH. Cedi)	−C	−C	+C	−1					=	0
Total Expenditures				+A	−1				=	0
Food Expenditures					+A	−1			=	0
Food Consumption						+A			=	0
Food energy Balance							+1		≤	B
Food energy requirement (BJ)							+1		=	0

Notes: C=Price coefficients; A=Technical coefficients; Y=Crop and Livestock yields; B=Available resource endowment. The values in the brackets are adjusted inside the model.

References

Berger, T., 2001. Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agric. Econ. 25, 245–260.
Block, P., Strzepek, K., Diao, X., 2008. Impacts of considering climate variability on investment decisions in Ethiopia. Agric. Econ. 39, 171–181.
Bobojonov, I., Hassan, A.A., 2014. Impacts of climate change on farm income security in Central Asia:an integrated modeling approach. Agric. Ecosyst. Environ. 188 (2014), 245–255.
Briner, S., Elkin, C., Huber, R., Grêt-Regamey, A., 2012. Assessing the impacts of economic and climate changes on land-use in mountain regions: a spatial dynamic modeling approach. Agric. Ecosyst. Environ. 149 (2012), 50–63.
Brooks, N., Adger, WN., Kelly, PM., 2005. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Glob. Environ. Change 15 (2), 151–163.
Claessens, L., Antle, J., Stoorvogel, J., Thornton, PK., Herrero, M., 2012. A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. Agric. Syst. 111, 85–95.
Clarke, D., Smith, M., El-Askari, K., 1998. CropWat for Windows: User Guide. University of Southampton, Southampton, UK, Available online at: http://tarwi.lamolina.edu.pe/~jgoicochea/Manuales/CROPWAT4W.pdf.
Conway, D., Schipper, F., 2011. Adaptation to climate change in Africa: challenges and opportunities identified from Ethiopia. Glob. Environ. Change 21, 227–237.
Deaton, A., Muellbauer, J., 1980. An almost ideal demand system. Am. Econ. Rev. 70 (3), 312–326.

De Pinto, A., Demirag, U., Haruna, A., Koo, J., Asamoah, M., 2012. Climate change, agriculture and food production in Ghana. International Food Policy Research Institute, Available online at: http://www.ifpri.org/publication/climate-change-agriculture-and-foodcrop-production-ghana.
Dercon, S., 2004. Growth and shocks: evidence from rural Ethiopia. J. Dev. Econ. 74, 309–329.
Deressa, T., Hassan, M., Ringler, C., 2007. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Glob. Environ. Change 19, 248–255.
Di Falco, S, Yesuf, M., Kohlin, G., Ringler, C., 2011. Estimating the impact of climate change on agriculture in low-income countries: household level evidence from the Nile Basin, Ethiopia. Environ. Resour. Econo. 52, 457–478.
Di Falco, S., Bulte, E., 2013. The Impact of Kinship Networks on the Adoption of Risk-Mitigating strategies in Ethiopia. World Dev. *4*, 100–110.
Di Falco, S., Chavas, JP., 2009. On crop biodiversity, risk exposure and food security in the highlands of Ethiopia. Am. J. Agric. Econ. 91 (3), 599–611.
Ellis, F., 2000. The determinants of rural livelihood diversification in developing countries. J. Agric. Econ. 51.2, 289–302.
Ghana Statistical Survey (GSS), 2004. Ghana Living Standard Survey Report (GLSS 4),1998/99. Accra, Ghana.
Gyasi, O., Schiffer, E., McCarthy, N., 2006. Community Needs Assessment and Local Water Governance Appraisal in the Upper East Region, Ghana (Draft, Submitted to EPTD Discussion Paper). International Food Policy Research Institute, Washington DC, USA.
Hertel, T., Burke, M., Lobell, D., 2010. The poverty implications of climate-induced crop yield changes by 2030. Glob. Environ. Change 20 (2010), 577–585.
Holden, S., Shiferaw, B., 2004. Land degradation, drought and food security in a less-favoured area in the Ethiopian highlands: a bio-economic model with market imperfections. Agric. Econ. 30 (1), 31–49.
Lodoun, et al., 2013. Changes in seasonal descriptors of precipitation in Burkina Faso associated with late 20th century drought and recovery in West Africa. Environ. Dev. 5 (2013), 96–108.
Marks, E., 2007. Validating Simulation Models: A General Framework and Four Applied Examples. University of New South Wales, Australia.
McCarl, B., Apland, J., 1986. Validation of linear programming models. South. J. Agric. Econ. 18, 155–164.
Milman, A., Arsano, J., 2013. Climate adaptation and development: contradictions for human security in Gambella, Ethiopia. Glob. Environ. Change.
Nedumaran, S., Berger, T., 2009. Impacts of Small Scale Irrigation on Poverty Dynamics in the White-Volta Basin of Ghana: An Integrated Multi-Agent Simulation Approach. Contributed paper prepared for presentation at the IHDP Open Meeting 2009 on Human Dimensions of Global Environmental Change. Bonn, Germany.
Nedumaran, S., Shiferaw, B., Bantilan, M.C.S., Palanisami, K., Wani, S.P., 2014. Bioeconomic modeling of farm household decisions for ex-ante impact assessment of integrated watershed development programs in semi-arid India. Environ. Devel. Sustain 16 (2), 257–286. (10.1007/s10668-013-9476-7).
Obeng, et al., 2013. Considering effective adaptation options to impacts of climate change for maize production in Ghana. Environ. Dev. 5 (2013), 39–53.
Oloukoi, et al., 2013. Households' coping strategies for climate variability related water shortages in Oke–Ogun region, Nigeria. Environ. Dev. 5 (2013), 23–38.
Sarpong, D.B., Anyidoho, N.A., 2012. Climate Change and Agricultural Policy y Processes in Ghana. Future Agriculture. Working paper.
Schilling, J., Freier, K.P., Hertig, E., Scheffran, J., 2012. Climate change, vulnerability and adaptation in North Africa with focus on Morocco. Agric. Ecosyst. Environ. 156 (2012), 12–26.
Schreinemachers, P., Berger, T., Aune, J., 2007. Simulating soil fertility and poverty dynamics in Uganda: a bio-economic multi-agent systems approach. Ecol. Econ. 64, 387–401.
Schreinemachers, P., Berger, T., 2011. An agent-based simulation model of human—environment interactions in agricultural systems. Environ. Modell. Softw. *26* (7), 845–859.
Seipt, et al., 2013. Capacity building for climate change risk management in Africa: encouraging and enabling research for informed decision-making. Environ. Dev. 5 (2013), 1–5.
Smith, M., 1992. CROPWAT—A computer program for irrigation planning and management. FAO Irrigation and Drainage Paper. 46.
Suri, T., 2011. Selection and comparative advantage in technology adoption. Econometrica *79* (1), 159–209, http://dx.doi.org/10.3982/ECTA7749.
Thornton, P.K., Jones, P.G., Alagarswamy, G., Andresen, J., 2009. Spatial variation of crop yield response to climate change in east Africa. Glob. Environ. Change 19 (1), 54–65.
Wheeler, T., von Braun, J., 2013. Climate change impacts on global food Security. Science 341, 508–513.
Woelcke, J., 2006. Technological and policy options for sustainable agricultural intensification in eastern Uganda. Agric. Econ. *34* (2), 129–139.
Yilma, T., 2005. (PhD thesis). Modeling Farm Irrigation Decision under Rainfall Risk in the White-Volta basin of Ghana.
Yilma, T., Berg, E., Berger, T., 2008. The agricultural technology-market linkage under liberalization in Ghana: Evidence from micro data. J. African Econ. 17 (1), 62–84.