How do African households adapt to climate change? Evidence from Malawi

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DRAFT VERSION

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Abstract

We use three waves of national representative household level panel data from Malawi to employ a structural model to estimate how households make land and labor allocation decisions in response to climate change. We first model the allocation of land to improved maize varieties as a function of precipitation history, input and output prices, household characteristics and extension advice and then estimate the welfare benefits associated with this decision in a household net income equation. This second stage also reveals the extent to which the household shift labor off-farm as total growing season precipitation fluctuates. We find that a 1% increase in intra-seasonal precipitation variability reduces household income by 1.5%. This effect falls to 1.3% after we account for the expected adjustment in improved maize adoption.

Introduction

Climate change is expected to affect food security and farm income in sub-Saharan Africa through its relationship to crop productivity. IPCC (2007) projects temperatures across Africa to increase 3-4$^{\circ C}$ over the course of this century (about one and a half times greater than the expected global temperature increase), and though rainfall projections are not uniform across the continent, Southern Africa is expected to receive less precipitation on average. Agronomic experiments indicate that this combination of heat and drought may cause significant yield reductions for most crops, specifically maize (Lobell et al., 2011). Analyses of actual crop output (as opposed to output under laboratory conditions) produce similar findings—Schlenker and Lobell (2010) measure the relationship between weather and observed country-level crop yields, predicting median yield losses of 8% for cassava and 22% for maize between now and 2050. Given the inertia in the climate system, some degree of climate change can be expected to set in regardless of the future path of CO_2 emissions (Smit and Pilifosova, 2001), and as such, adaptation to these inevitable changes represents the only feasible short-run strategy. Understanding the nature of effective adaptation and quantifying its welfare impact remains a critical task in the study of climate change in sub-Saharan Africa. We contribute to this line of research using household-level evidence from Malawi.

This study's objective is first, to uncover the relationship between climate and improved maize adoption among Malawi farmers, and second, to understand how this planting decision shapes the impact of climate change on household income. We define climate in terms of growing season precipitation, specifically 1) cumulative growing season precipitation and 2) rainfall variation within the growing season. Furthermore, we define the intensity of improved maize adoption in terms of the share of cultivated land planted with improved maize varieties. Determining the structure of these relationships between climate and farm management practice allows for an evaluation of climate change impacts that explicitly accounts for expected adjustments in the use of improved maize varieties. This facilitates a direct comparison of the welfare effects of climate change with and without this behavioral adjustment, letting us quantify the benefits of the adaptation strategy. We construct a structural model of adaptation and production decisions which allows us to gauge the overall effect of climate change on farmers' welfare and identify the mechanisms through which this effect unfolds. In particular, farmers may react to climate change by adopting adaptation strategies or reallocating inputs and outputs according to technological possibilities and market conditions. Our framework, consisting of a structural model estimated with panel data, allows us to distinguish between the two mechanisms which is, in turn, critical for assessing the effectiveness of adaptation strategies on alleviating the adverse impacts of climate change on farmers' well-being.

Past economic assessments of climate change impacts have not adequately accounted for the role of human behavior to fully or partially offset the effects of environmental change. Initial studies utilized known agronomic relationships to forecast the response of crop yield to various changes in rainfall and temperature, though they lack a proper model of economic incentives (Easterling et al., 1992a; Rosenzweig and Parry, 1994). Later analyses used cross-sectional variation in land values to estimate the monetary value of long-run shifts in climate variables, implicitly accounting for adjustments in the activities taking place on that land but failing to delineate any particular adaptations, nor explaining how such adjustments might occur (Mendelsohn, 1994). More recently panel data sets have been used to estimate the response of yearly profit to random year-on-year weather fluctuations (Deschenes and

Greenstone, 2007; Guiteras, 2009). While these analyses account for efficient adjustments to growing season weather within a particular year, they do not allow for more substantial changes in input or output mix that could be rational under different climate conditions. Finally, other studies look in detail at farmers' economic perceptions of past weather patterns and their reported economic responses to those patterns (Maddison, 2007; Gbetibouo et al., 2010; Deressa et al., 2011). These studies often neglect to examine the degree of adaptation undertaken and rarely incorporate prices into the adaptation decision. None of the research mentioned above explicitly models climate change adaptation as a function of input and output prices, nor does it measure the welfare gain associated with any particular behavioral response.

Di Falco et al. (2011a), using a cross-sectional data set from Ethiopia, investigate the drivers of household-level climate change adaptation and estimate the effects of adaptation on household food security. Adaptation is modeled as a binary variable equal to one if the household adapted and zero otherwise, which is then regressed on household characteristics, asset ownership, soil quality and erosion, occurrences of drought or flood, and climatic measures to uncover the drivers of this behavior. They identify 1) credit access and 2) access to information about climate and farm practices to be correlated significantly with adaptation. In order to correctly attribute food production outcomes to adaptation rather than to unobserved household characteristics, they employ an endogenous switching model to produce counterfactual scenarios—that is, they estimate what the productivity of adapting households would have been in the event that they had not adapted and vice versa for non-adapting households.

Our study improves on this Di Falco et al. (2011) in two specific ways. First, since adaptation enters their model as a 'yes/no' decision, their analysis is unable to differentiate between adaptation strategies and cannot account for the intensity with which these strategies are adopted. Second, while they attempt to isolate the effect of the adaptation by constructing a counterfactual outcome, their use of cross-sectional data makes it difficult to adequately disentangle the effect of the adaptation itself versus the propensity to adapt, which itself may affect the outcome (food security). Moreover, cross-sectional data sets are not ideal instruments for measuring adaptation, which is inherently a time-series phenomenon. Our study addresses this first concern by identifying two relevant adaptation strategies that we model as continuous variables: 1) changing the share of cultivated area planted with improved maize varieties and 2) shifting the amount of labor that the household allocates to off-farm work. We address the second concern by using a household-level panel data set of from Malawi. Our model's first stage measures the impact of changes in cumulative growing season precipitation on the share of land allocated to improved maize varieties conditional on prices, household characteristics, and extension advice. We insert predicted values from stage one into a stage two profit equation to compute adaptation's effect on net household income. In the process we derive off-farm labor supply as a function of growing season rainfall. This framework allows for explicit modeling of climate change adaptation and an evaluation of the welfare implications.

Literature Review

In what follows we describe previous methods of climate change impact assessment. Broadly, these approaches include those that focus exclusively on the relationship between crop yield and weather variables (the agronomic approach), those that use existing cross-sectional relationships between climate and land values to project future impacts (the Ricardian approach), those that measure the effect of random weather fluctuations on yearly profit (panel data studies), and those that illicit direct responses from farmers about their behavioral adjustments to perceived climate change (adaptation studies).

Agronomic Approach

Since climate is a key determinant of agricultural productivity, studying the interaction between climate and agricultural yield constitutes a reasonable starting point for measuring climate change welfare impacts. Combining estimations of these agronomic properties with climate forecasts give an approximate measure of the expected yield losses (or gains) associated with future shifts in temperature and rainfall. Early attempts to predict the economic impacts of climate change in this manner include Adams et al. (1988a), Adams (1989), Easterling et al. (1992a), Easterling et al. (1992b) and Rosenzweig and Parry (1994). These approaches do not consider adaptation in any systematic way. Climate is modeled as an input to the agricultural production process, and when adaptation is acknowledged, it enters the simulation as a set of parameters that can be adjusted at the researchers' discretion. Often agronomic experts are consulted to suggest reasonable adaptation strategies, but a more realistic approach would have these adaptations dictated by changes in relative prices rather than imposing them artificially.

Ricardian Approach

Following Mendelsohn et al. (1994), researchers have employed a Ricardian framework to estimate the welfare implications of long-run climate change and subsequent adaptation (Deressa, 2007; Sanghi and Mendelsohn, 2008; Wang et al., 2009). While the agronomic approach holds fixed all inputs, outputs and technology, the Ricardian method represents an attempt to measure the residual climate change impact after individuals have fully adjusted all inputs and outputs to maximize profit given their new conditions. Underlying the analysis is the theory, formally articulated by David Ricardo, that land value under properly functioning land markets will equal the present value of the infinite profit stream accruing to the owners of that land. Mathematically, land value or annual net revenue is expressed as a function of exogenous climate variables, allowing the analyst to calculate the change in welfare associated with a given change in those exogenous climate parameters. The technique takes advantage of spatial variation in climate at a point in time to estimate how climate change might influence the profitability of agricultural land. Land value (or annual profit) is regressed on a set of climate variables (usually monthly averages temperature and precipitation across a 30-year period) along with other variables like soil type, altitude, and household characteristics to control for non-climatic factors that might explain land value. Parameter estimates are then combined with output from a climate change forecast to predict the income loss due to future climate change. While the Ricardian model assumes adaptation, it does not reveal anything about the adjustment process—only the final outcome (land value or annual net revenue) is observed.

More recently, a "structural Ricardian" framework has been developed for the purposes of modeling adaptation explicitly. Like the standard Ricardian approach, the structural model estimates long-run welfare impacts of climate change, but it includes an intermediate step that predicts behavioral changes that might occur along the way. The model's first stage involves an estimation of the likelihood of choosing a particular farm practice (among a set of practices selected beforehand by the researcher) conditional on climate, soil, and socio-economic factors. The second stage calculates the net revenue associated with that farm practice. This produces a mathematical relationship between climate variables and net revenue conditional on the choice of production activity. Once climate change forecasts are introduced into the equation, the results show not only the expected final outcome, but also reveal expected adjustments made by the farmers to better suit the new conditions (say, switching from a specialized crop farm to an integrated farm with both crops and livestock). The structural approach is more transparent about the process by which a farmer might reposition himself in the new climate, but it still suffers from problems associated with using cross-sectional data to analyze a time-series process. The model almost certainly does not capture the full range of adaptations available to the farmer, nor does it account for constraints that might prevent efficient adaptation.

Panel Data Studies

Panel data studies fall somewhere between the agronomic and Ricardian approaches with respect to their assumptions about the flexibility of farm management decisions—they measure the response of farm profit or agricultural yield to random, year-to-year weather fluctuations (Schlenker and Roberts, 2006; Schlenker et al., 2006; Deschenes and Greenstone, 2007; Guiteras, 2009; Schlenker and Lobell, 2010; Deschenes and Greenstone, 2011). While farmers are free to adjust some inputs during the course of the year in response to the conditions they observe, the time frame is too short to undertake the full range of adaptations that might be beneficial in the face of long run climate change. In terms of the validity, the relevant question is as follows: is long-run climate change comparable to yearly weather fluctuations or are the two phenomena qualitatively different? If long-run climate change is believed to be just a 'scaled-up' version of yearly variations, then the panel approach will approximate climate change impacts. If this is not the case, then its validity is called into question. While intra-seasonal adaptation is implicit in the dependent variable (farmers are assumed to choose the levels inputs that earn them the highest net return), the model does not reveal the details of this adjustment process. As with the Ricardian method, only the outcome is observed.

Adaptation Studies

The structural Ricardian approach portrays how farmers' current practices vary across different climates, allowing the researcher to forecast adaptation practices by examining spatial analogues (Tol, Fankhauser and Smith, 1998). However, this technique assumes that farmers will adapt, ignoring the possibility that certain segments of the population may be significantly less likely to adapt efficiently or expediently. Another approach to climate change adaptation research, which we refer to as "adaptation studies," tries to shed light on the factors that influence adaptive capacity (Hassan and Nhemachena, 2008; Deressa et al., 2009; Deressa et al., 2011; Fosu-Mensah et al. (2012). These studies generally ask farmers open-ended questions regarding 1) their perceptions of climate change, 2) adaptations they've already undertaken, and 3) factors that prevent them from adapting further (or at all). Responses are categorized and regressed on a set of household and village characteristics to estimate the relative importance of various social, economic, or institutional factors in affecting adaptation choices. A weakness of these studies is that most of them do not attempt to associate the adaptation outcomes with a welfare measurement, that is, they suggest that constraints are present but do not estimate how much better off households would be if barriers were eliminated. Self-reported perceptions of climate change and adaptive responses is inherently less precise than weather records used in Ricardian studies, but this qualitative information provides a richer description of the set of possible adaptations and suggests relevant constraints that might prevent efficient behavior.

Di Falco and Veronesi (2012) (DV henceforth) produce what might be the most cutting edge quantitative analysis of the determinants of adaptation to climate change and their welfare implications. They identify three distinct forms of adaptation—(1) changing crop varieties, (2) implementing water strategies (water harvesting, water conservation, or irrigation), and (3) implementing soil conservation—and define the choice set as nine mutually exclusive strategies (any of (1), (2), or (3) adopted in isolation;

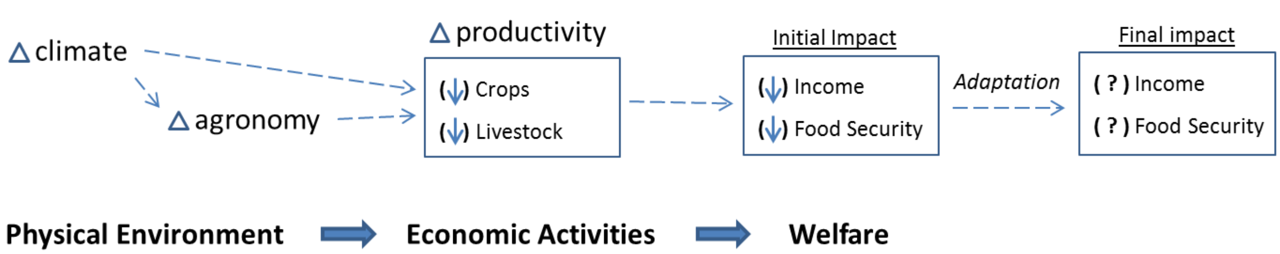
any pairwise combination of (1), (2) and (3); implementing all three together; implementing other strategies; or no adaptation). With the adaptation variables defined, they construct a multinomial logit regression model to uncover the effect of long-run temperature and precipitation on the adaptation decision and to determine the extent to which other factors (household and farm characteristics, the presence of assets, and the experience of previous extreme weather events like drought or flood) explain the adoption of a particular strategy. In a second phase, they estimate expected net revenue conditional on the adaptation choice as well as a counterfactual outcome, following a procedure used in Di Falco et al. (2011a). Their results show that strategies adopted in isolation are ineffective, while adopting them in combination produces positive and significant benefits (curiously, they find that adopting all three strategies at once produces less benefit than any pairwise combination).

An important shortcoming of DV's analysis is that it ignores intensity of adaptation. While forms of adaptation are differentiated to an extent, adoption remains a binary outcome. As such, crucial information is lost regarding how net farm revenue might respond to varying degrees of adoption. For example, the benefits of irrigation would depend greatly on the extent to which it was used, rather than simply whether it was adopted or not. Secondly, even though adaptation is inherently a time-series phenomenon (conditions change and individuals react in turn), research that has quantitatively analyzed the adaptation process using panel data remains scarce. DV's use of cross-sectional data makes it possible that certain unobservable differences between households were not adequately controlled for. These two issues constitute a substantial gap in the study of climate change adaptation. With regard to the first consideration, we fill this gap by modeling adaptation as a continuous variable so as to estimate how welfare might be enhanced by changes in farming practice on the margin. With respect to the second, we have access to a panel data set from Malawi which will allow us to produce estimates that more reliably control for unobservable differences between households. Our objective is to identify adaptation measures that are currently being undertaken in Malawi in response to climate change and to quantify the welfare gains associated with those measures.

Model

The ultimate impact of environmental change on people's lives will be mediated through the behavioral adjustments they make in response to the physical stimulus. Figure 1 illustrates this process. On the far left, a change in the climate is introduced, which in turn alters crop and livestock productivity. The diagram assumes that productivity is reduced, though this need not be true in general. The impact on productivity affects welfare by reducing income and food security. These impacts correspond to the individual's initial production practices, that is, the calculation assumes that the household maintains the same production decisions as before the climate shift. Such an assessment is essentially equivalent to measuring the relationship between climate and crop or livestock productivity, and converting the climate-induced output reduction into monetary terms. A more complete analysis should extend the calculation one step further, accounting for the behavioral response that is likely to follow and estimating the final impact on income or food security after the individual has had the opportunity to adjust. Since these adjustments are voluntary, one expects that they improve the household's position by offsetting some fraction of the damages brought about by the climate shift (though the magnitude and of the final impact is uncertain). It is conceivable that the climate shift creates economic opportunities that had not previously existed and thus the household is actually made better off following the climate shift and subsequent adaptation. The final outcome will depend on the nature of the climate stimulus, the effect of that stimulus on production processes, and on the individual's capacity to transition from one activity to another.

Figure 1.



Mathematically, we can express the process illustrated in Figure 1 as follows. Let profit π be a function of climate and some characteristic of the production process, z, that can be adjusted to suit the climate conditions.

$$(1)\ \pi = f(climate,\ z)$$

The state of the climate is exogenously given, but z is a choice variable. Assuming that the household chooses z such that profit is maximized, the optimal choice of z will be a function of climate.

$$(2)\ \pi^* = f\{climate,\ z^*(climate)\}$$

Differentiating π with respect to climate gives the change in profit for small changes in climate, which is composed of the direct partial effect of climate on profit and the indirect partial effect of climate on profit through adaptation:

$$(3)\ \frac{d\pi}{d(climate)} = \frac{\partial\pi}{\partial(climate)} + \frac{\partial\pi}{\partial z} \times \frac{dz}{d(climate)}$$

Our aim is to identify z and pin down the functional relationships in (1) so as to derive the structure of equation (2). Once (2) is obtained we can apply climate change projections to arrive at the expected net climate change impact.

Identifying z

Adaptation measures that appear most frequently in recent climate change adaptation studies fall broadly into four categories: switching crop varieties, crop diversification, diversification across crop and livestock production, and diversification across farm and non-farm activities. Table 1 lists studies that explicitly model these behaviors or refer to these forms of adaptation as being particularly common or effective. In terms of the frequency with which they appear, switching crop varieties and supplementing farm income with off-farm income seem to be the most relevant adaptation strategies. We thus define adaptation with respect to two particular farming decisions: first, the share of cultivated area planted with improved maize varieties and second, the share of time during the year allocated to off-farm work. Both behaviors are consistent with the definitions of adaptation that have appeared in previous research and both constitute shifts on the intensive margin (i.e. a household increases the productivity of its existing stock of land and labor by switching seed varieties and adjusting fertilizer application in the former case and allocating existing labor where it earns a higher return in latter case). With considerable friction in African markets for land and labor, we believe it makes sense to concentrate our analysis on this intensive margin. Finally, in contrast to models that construct adaptation as a binary decision (adapt or not), these two adaptation variables are continuous between zero and one, allowing for a more nuanced analysis of how incremental changes in these types of behavior affect household welfare. Understanding how varying degrees of adaptation impact welfare provides more precise policy recommendations.

Table 1. Prominent Climate Change Adaptation Measures in the Literature

Switching crop varieties

Desanker, Magdza et al. (2001)	Molua (2002)	Kurukulasuriya and Rosenthal (2003)
Behnin (2006)	Thomas et al. (2007)	Maddison (2007)
Mertz et al. (2009)	Apata et al. (2009)	Bryan et al. (2009)
Deressa et al. (2009a)	Deressa et al. (2009b)	Mutekwa (2009)
Below et al. (2010)	Gbetibouo et al. (2010)	Burke and Lobell (2010)
Yamauchi et al. (2010)	Di Falco et al. (2011a)	Di Falco et al. (2011b)
Molua (2011)	Fosu-Mensah et al. (2012)	Di Falco and Veronesi (2012)

Crop diversification

Desanker, Magdza et al. (2001)	Behnin (2006)	Kurukulasuriya and Mendelsohn (2008)
Dinar et al. (2008)	Seo and Mendelsohn (2008)	Bryan et al. (2009)
Mertz et al. (2009)	Mutekwa (2009)	Apata et al. (2009)
Gbetiouo et al. (2010)	Burke and Lobell (2010)	Fosu-Mensah et al. (2012)
Silvestri et al. (2012)		

Diversification across crop and livestock production

Desanker, Magdza et al. (2001)	Behnin (2006)	Thomas et al. (2007)
Mendelsohn and Seo (2007)	Dinar et al. (2008)	Hassan and Nhemachena (2008)
Seo (2010a)	Seo (2010b)	Di Falco et al. (2011a)
Di Falco et al. (2011b)	Di Falco and Veronesi (2012)	Silvestri et al. (2012)

Diversification across farm and non-farm activities

Kurukulasuriya and Rosenthal (2003)	Maddison (2007)	Boko et al. (2007)
Shewmake (2008)	Dinar et al. (2008)	Apata et al. (2009)
Mutekwa (2009)	Below et al. (2010)	Burke and Lobell (2010)
Deressa et al. (2010)	Di Falco et al. (2011a)	Di Falco et al. (2011b)
Molua (2011)	Fosu-Mensah et al. (2012)	Di Falco and Veronesi (2012)
Silvestri et al. (2012)		

Stage one: Linking climate and z

Pauw et al. (2010) estimate the impact of drought on maize production in Malawi allowing for varying degrees of improved maize adoption. They find that shifting 10% of cultivated area from local maize varieties to commercial varieties fully offsets the yield losses associated with a mild drought (a drought that would recur every five years on average) and partially offsets those associated with more severe droughts (those with return periods of 10 years or more). It is therefore reasonable to expect a shift from local varieties to improved varieties as Malawi's climate becomes hotter and drier, provided that farmers have proper weather information and access to these improved seeds. Prior to estimating a household net income equation, we examine this relationship between climate and the household's share of land planted with improved maize varieties.

Improved maize share is modeled as a function of 30 year weather history (including means and variances), recent weather shocks, input and output prices, and other characteristics of the household.

(4) $$z_1 = f(w_1, w_2, \dots, w_{21}),$$ where

z_1 is the area planted using improved maize seed varieties divided by total cultivated area,

w_1 is wealth as measured by the value of livestock and durable goods owned,

w_2 is cumulative growing season precipitation averaged across the 30 years preceding the observation year,

w_3 is w_2 squared,

w_4 is the coefficient of variation of cumulative growing season precipitation over the 30 years preceding the observation year,

w_5 is w_4 squared,

w_6 is the coefficient of variation of monthly rainfall within the growing season averaged across the 30 years preceding the observation year,

w_7 is w_6 squared,

w_8 is binary variable equal to one if the household reported to be severely impacted by an extreme rainfall pattern in the past five years and zero otherwise,

w_9 is the previous year's maize price,

w_{10} is the price of commercial fertilizer in the current year,

w_{11} is the amount of subsidized fertilizer acquired by the household in the current year,

w_{12} is the wage rate for ganyu labor in the current year,

w_{13} is a binary variable equal to one if the household purchased inputs with credit during the growing season and zero otherwise,

w_{14} is a binary variable equal to one if the household head is female and zero otherwise,

w_{15} is household size as measured by adult equivalent,

w_{16} is household landholding,

w_{17} is a binary variable equal to one if the household reported to have received useful advice on new seed varieties,

w_{18} is the price of improved maize seed,

w_{19} is a binary variable equal to one if the observation corresponds to the 2003-2004 growing season

w_{20} is a binary variable equal to one if the observation corresponds to the 2006-2007 growing season

w_{21} is a binary variable equal to one if the observation corresponds to the 2008-2009 growing season

We construct the equation for household i at time t as follows, where α_i represents time-invariant, household-specific fixed factors and ε_{it} represents unobserved household-specific factors that vary across time.

$$(5)\ z_{it} = \beta_1 w_{it1} + \beta_2 w_{it2} + \cdots + \beta_{14} w_{it14} + \alpha_i + \varepsilon_{it}\ ,\ \ t = 1, 2, 3$$

After time-demeaning all the variables in (5), we estimate a fixed effects regression model to uncover the importance of these right-hand side variables in explaining improved maize share, controlling for unobservable, time-invariant factors.

Hypotheses

The effect of wealth on the intensity of improved maize adoption could conceivably go in either direction. On the one hand, if wealthier farmers engage in a more diverse portfolio of activities, they may devote a smaller share of their resources to crops and thus not be particularly concerned about minimizing risk in the domain of maize production (Kaliba et al., 2000). Using livestock ownership as a proxy for assets, Deressa et al. (2009) find a negative (though statistically insignificant) relationship between livestock ownership and the adoption of new crop varieties. On the other hand, household wealth might provide greater capacity to learn about and acquire new varieties and also serve as a safety net in case the new practices fail. In the same vein, a poorly-endowed farmer 1) may be especially averse to the risk associated with switching to a new technology, 2) may not have the access to complementary inputs, or 3) may not be informed concerning proper management techniques. In these cases, we'd expect wealth to be positively related to share of improved maize. Gbetibouo et al. (2010) find that the probability of adapting to climate change increases with wealth; in particular, wealthier households were more likely to change planting dates. Regarding maize more specifically, Sserunkuuma (2005) finds higher improved maize adoption among households with higher measured livestock value. Bellon and Risopoulos (2001) construct a 'wealth ranking' system and find the intensity of improved maize adoption to be significantly lower among households classified as 'poor' as compared to the rest of the sample. Langyintouo and

Mungoma (2008)'s analysis of improved maize adoption in Zambia suggests that wealth is positively related to the intensity of adoption. Gauging this positive effect to be stronger, we hypothesize a positive sign for β_1.

We reason that households use historical weather information to predict conditions in the upcoming growing season and, in turn, this expectation informs their planting decisions. However, it is not clear how they view long-run means relative to recent short-run patterns. Do they consider 30-year average weather to be the best estimator for next season's conditions, or do they place greater weight on the most recent three to five years?[1] Previous climate change studies almost without exception define climate as 30-year weather history. We adopt this definition, while also testing shorter time horizons to determine the sensitivity of the results to changes in this specification. Our climate variables include cumulative growing season precipitation averaged across the 30 years immediately preceding the observation year, the coefficient of variation of total growing season rainfall over those same 30 years and the coefficient of variation of monthly rainfall within the growing season averaged across 30 years. Because farmers tend to be risk averse, we expect that the adoption of improved maize varieties will intensify as growing seasons become drier and as variability increases both within and across years. However, the fact that we specify these variables in quadratic form makes it difficult to predict the signs in advance, thus we do not hypothesize signs for β_2 through β_7.

A recent occurrence of bad weather might also induce the farmer to adopt a crop variety that is more resilient under unfavorable conditions. We account for this by including a binary variable equal to one if the household reported to be severely impacted by an extreme rainfall pattern in the past five years and zero otherwise. We expect β_8 to be positive.

In general, the price of an output should spur the production of that output, and increase demand for that good's inputs. Specifically, an increase in the price of maize should result in an expansion of area

[1] In a stable climate, more past observations will always improve the estimate for next year's conditions, but when climate is shifting, it may not be useful to look far into the past where the underlying parameters of the climate system were different than today.

planted with maize, but it is not obvious how this new area will be split between improved maize varieties and local maize varieties. Because improved maize varieties tend to be more productive overall (Morris et al., 1999), it would be reasonable to expect an increase in maize output price to accelerate the adoption rate for improved varieties. In one of the few studies to include maize output price as an explanatory variable for improved maize seed adoption, Mwabu et al. (2006) verify this hypothesis in Kenya, but due to the scarcity of empirical evidence, we leave the sign of β_9 unspecified a priori.

An increase in the price of an input ought to reduce the quantity demanded of that input and other complementary inputs, but if fertilizer interacts with improved maize varieties in exactly the same manner as with standard varieties, then we would not expect to find a relationship between fertilizer price and improved maize adoption. On the other hand, if fertilizer and improved maize are believed to be strongly complementary, then we would expect that an increase in fertilizer price would reduce improved maize share. Nkonya et al. (1997) and Amaza et al. (2008) both uncover a positive and significant correlation between fertilizer application and the area planted to improved maize varieties, lending credence to this hypothesis. Ogunlade et al. (2010) identify lack of access to fertilizer as a barrier to optimizing the benefits of improved maize varieties. Based on these findings, we hypothesize a negative sign for β_{10}. Following the same logic, we expect access to subsidized fertilizer to correlate positively with improved maize share, resulting in a positive sign for β_{11}.

Since off-farm labor is substitute for maize production, we would expect that a higher wage rate would result in more off-farm work and less attention crop activities. However, because our dependent variable is expressed in terms of share instead of levels, it is a bit ambiguous whether the *share* of improved maize production would necessarily decrease as off-farm work becomes more profitable. We do not specify a sign for β_{12} in advance.

Access to credit ought to relax any liquidity constraints the household may face and thus enhance adaptive capacity. Credit has been found to increase the likelihood of adaptation generally (Fosu-Mensah et al., 2012; Bryan et al., 2009; Deressa et al., 2011), as well as for improved maize seed adoption (Amaza et al., 2008; Langyintuo and Mekuria, 2008; Feleke and Zegeye, 2006; Paudel and Matsuoka, 2008). We hypothesize a positive sign on β_{13}.

The empirical evidence on the impact of the household head's gender on adaptation is mixed. Some analyses detect a positive relationship between male headed households and the likelihood of switching crop varieties in response to perceived climate change (Deressa et al., 2009; Deressa et al., 2011), while Bayard et al. (2007) finds a greater likelihood of adopting alley cropping among female farmers. Other studies find no significant effect of gender on adoption of improved maize (Chirwa 2005; Langyintuo and Mungoma, 2008; Etoundi and Dia, 2008) or on any form of climate change adaptation (Gbetibouo et al., 2010; Fosu-Mensah et al., 2012; Silvestri et al., 2012). We do not specify a sign for β_{14} beforehand.

Higher yielding maize varieties often require more labor input than ordinary varieties (Feder at al. 1985), so theoretically, a larger household should be more capable of adapting in this way due to their higher labor endowment. Empirically, Hassan and Nhemachena (2008), Bryan et al. (2009) and Deressa et al. (2011) report significant positive effects of household size on generic climate change adaptation, and Feleke and Zegeye (2006) also find a positive effect looking specifically at improved maize adoption. Family labor did not have a significant impact on improved maize adoption in the analyses of Langyintuo and Mungoma (2008), Paudel and Matsuoka (2008), Nkonya et al. (1999) and Kaliba et al. (2000). On the other hand, Amaza et al. (2008) uncover a negative impact of family size on improved maize adoption in Nigeria, theorizing that larger households are involved in a greater diversity of activities and place less importance on crop production. Owing to the conflicting empirical evidence, we do not hypothesize a sign for β_{15}.

Farm size is believed to be positively related to adaptive capacity because adopting new technology incurs fixed costs that are more easily absorbed by larger entities—the greater the fixed costs associated with the adoption of a particular measure, the greater the size threshold (Daberkow and McBride, 2003; Just et al., 1980). Though not specifically analyzing the adoption of new crop varieties, Bryan et al. (2009) uncover a positive relationship between landholding and the likelihood of adaptation to climate change in South Africa and Ethiopia. While evidence is somewhat mixed, the majority of analyses report a positive correlation between farm size and improved seed adoption. In the sample analyzed by Etoundi and Dia (2008), larger farm size reduced the probability of adopting the 'CMS 8704' maize variety in Cameroon. Similarly, Langyintuo and Mungoma (2008) uncover a negative relationship between farm size and the intensity of improved maize adoption in Zambia. On the other hand, Sserunkuuma (2005), using a sample from Uganda, suggests that larger farms have higher adoption rates of improved maize. Nkonya et al. (1997), Simtowe et al. (2009), Langyintuo and Mekuria (2008) and Iqbal et al. (1999) corroborate this latter finding; thus, our initial belief is that β_{16} should be positive.

Numerous studies have found that access to agricultural extension services increases the likelihood of adaptation (Bryan et al., 2009; Feleke and Zegeye, 2006; Kaliba, et al., 2000; Gbetibouo et al., 2010; Languintuo and Mekuria, 2008; Ransom et al., 2003; Tura et al., 2010). We attempt to control for access to information and seeds by including a binary variable equal to one if the household reported to have received useful advice regarding new seed varieties. We expect β_{17} to be positive.

Stage two: Linking climate and π

The results of any climate change impact assessment depend critically on assumptions about the flexibility of households to adjust input use or switch technology. Consider the following example. Suppose profit (π) is a function of three inputs, two of which are farm decisions while the third is outside the farmer's control. Let the two choice variables be called capital (K) and labor (L) and call the exogenous factor precipitation (P), which affects the productivity of the first two. We have $\pi = f(L, K, P)$. Since the productivity of labor and capital depend on rainfall levels, the optimal choices of K and L will be functions of P. The household will choose levels of capital and labor to suit the prevailing rainfall conditions, which results in $\pi^* = f[L^*(P), K^*(P), P]$. Using this simple profit function, we can examine the welfare implications of a change in precipitation under different degrees of input flexibility. Let $\bar{P}$ denote initial precipitation, let $\bar{L}$ and $\bar{K}$ denote inputs levels optimized for $\bar{P}$, and let $\bar{\pi}$ denote the profit earned at these initial levels.

$$\bar{\pi} = f(\bar{L}, \bar{K}, \bar{P})$$

Suppose $\bar{P}$ shifts to P', while both labor and capital are fixed at $\bar{L}$ and $\bar{K}$, respectively. Let π_1 be function mapping any P' to the level of profit earned conditional on $\bar{L}$ and $\bar{K}$. This function describes the welfare impact of climate change absent of any behavioral adjustment. Because capital and labor were optimized for the previous rainfall pattern, profit will decrease for any $P' \neq \bar{P}$. Simulating climate change impacts using π_1 is commensurate with the 'agronomic' approach (i.e., calculating the direct response of crop yield to one or more climate parameters, holding technology and inputs usage fixed).

$$\pi_1 = f(\bar{L}, \bar{K}, P')$$

If we allow flexibility in L, the profit maximizing household will adjust labor employment to suit P', thereby offsetting some of the climate change impacts. Let L' denote optimal labor use given P' and fixed $\bar{K}$, and let π_2 describe the relationship between P' and profit given that the household can vary its labor input (though still holding capital fixed). In choosing L' over $\bar{L}$, the household can be no worse off and likely sees a welfare improvement.

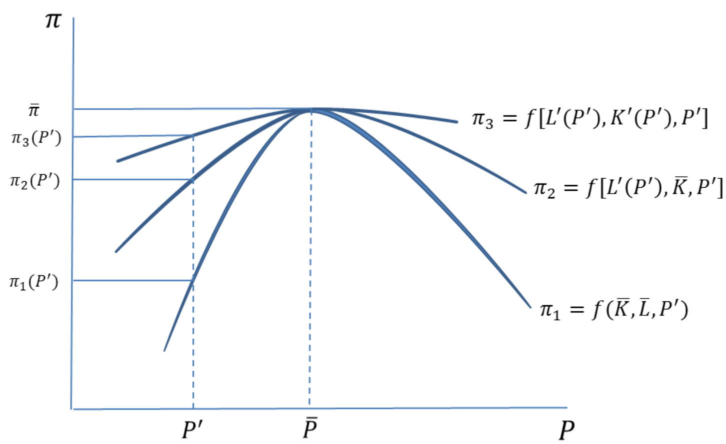
$$\pi_2 = f[L'(P'), \bar{K}, P']$$

Finally, allowing for the adjustment of both labor and capital, the household's capacity to mitigate damages is even greater. Let K' denote the optimal usage of capital given P', and let π_3 describe the household's optimal profit for any level of rainfall. The relationship between profit and rainfall in π_3 can be used to simulate the impact of climate change accounting for all adaptations. This corresponds to the 'Ricardian' approach, where all future adaptations are capitalized in land values.

$$\pi_3 = f[L'(P'), K'(P'), P']$$

An important property of these three functions is that $\pi_3 \geq \pi_2 \geq \pi_1$ for all P', which is consistent with our intuition—increasing degrees of freedom can never make the household worse off and will almost certainly facilitate an improvement. The impacts of a shift to P' with no adaptation are given by $\pi_1(\bar{L}, \bar{K}, P') - \bar{\pi}(\bar{L}, \bar{K}, \bar{P})$, while the impacts for the same shift under perfect adaptation are given by $\pi_3[L'(P'), K'(P'), P'] - \bar{\pi}(\bar{L}, \bar{K}, \bar{P})$. Because $\pi_3 \geq \pi_1$, total damages are smaller in the case where all inputs are variable; Figure 2 illustrates this comparison.

Figure 2.



The intermediate case (π_2) is exemplified in Deschenes and Greenstone (2007) (henceforth DG) and Guiteras (2009), where annual outcomes (profit in the former study, crop yield in the latter) are modeled as functions of growing season weather. Assuming that farmers optimally modify their input use as the growing season unfolds, this yearly profit or yield measurement takes account of all adaptations made within the growing season. Such changes might include adjustments in labor effort or fertilizer application, which are carried out in response to the weather conditions during a particular year. Estimating this relationship yields a function resembling π_2 where labor is free to adjust, but capital is fixed at $\bar{K}$. If climate change takes the form of small, steady changes that reflect the historical trend, then this technique will closely approximate future impacts. However, this method cannot predict structural changes that might occur in response to a qualitatively different climate. For instance, suppose rainfall continues its gradual decline to the point that in-season adjustments become increasingly less effective. At this juncture, the farmer may need to adopt some form of irrigation technology in order to remain viable (which is analogous to shifting form $\bar{K}$ to K' in our illustration). Doing so will offset a portion of the damages, but such an effect will not appear in the impact analysis because the model (π_2) did not foresee the adoption of this technology. The relationship between rainfall and profit in π_2 will not be valid for a household that makes this kind of switch.

DG and Guiteras (2009) both acknowledge these limitations, but emphasize that π_2 is a substantial improvement over π_1 and, given the inherent uncertainty associated with detecting climate signals, may prove quite accurate. Considering that climate is characterized by a distribution of possible outcomes rather than a specific event, 10 or 15 years may be required to distinguish true climate shifts from random year-on-year fluctuations. This detection problem necessarily implies that climate change adaptation will be slow; moreover, uncertainty about the permanence of various weather phenomena will make large investments risky. The longer these adaptations are delayed, the better these estimates in π_2 will approximate the true impact. Furthermore, in the event that more sophisticated adaptations occur, the estimates given in π_2 will overstate the damages; in this way, the results represent an upper bound.

We follow DG's approach by studying the sensitivity of profit to growing season conditions. Since our profit function includes input and output prices, we control for the influence of these exogenous factors on profit, isolating the partial effect of growing season weather on profit. Applying climate change projections to this estimated relationship gives an approximate measure of climate change impacts. This approach still suffers from the fact that large changes in climate will bring about adaptations that our model leaves out, but we improve on DG's methodology in two ways. First, we include input and output prices in the profit equation, allowing us to derive a system of supply and demand equations. Estimating this system simultaneously increases the efficiency of our parameter estimates. Second, we explicitly model the adoption of improved maize, providing a more complete description of farmers' behavioral response. This information contributes to the investigation of factors that influence improved maize adoption, while at the same time, improving the reliability of climate change impact assessment.

We model net household income as follows. After optimization, profit depends only on a vector of prices $\boldsymbol{p}$ and fixed inputs $\boldsymbol{z}$.

(5) $\pi^* = f(p_y,\ p_1,\ p_2,\ p_3,\ z_1,\ z_2,\ z_3,\ z_4,\ z_5)$, where

p_y is the wage-rate for off-farm labor

p_1 is the price of maize

p_2 is the price of fertilizer

p_3 is the price of hired labor

z_1 is the share of cultivated land planted with improved maize varieties

z_2 is cumulative growing season precipitation

z_3 is the coefficient of variation of monthly growing season precipitation

z_4 is household assets as measured by the value of livestock and durable goods

z_5 is total household landholding

After optimization, output supplies (y and x_1) and input demands (x_2 and x_3) become functions of prices and fixed inputs:

(6) $y^* = f\left(p_y,\ p_1,\ p_2, p_3,\ p_4,\ z_1,\ z_2,\ z_3,\ z_4,\ z_5\right)$

(7) $x_i^* = f\left(p_y,\ p_1,\ p_2, p_3,\ p_4,\ z_1,\ z_2,\ z_3,\ z_4,\ z_5\right)$ for i = 1, 2, 3

where y is the quantity of off-farm labor supplied

x_1 is the quantity of maize sold (which is a function of variable inputs x and fixed inputs z)

x_2 is the quantity of fertilizer purchased

x_3 is the quantity of labor hired

Like DG, our profit function resembles π_2. Our model allows for intra-seasonal adjustments in off-farm labor supply, hired on-farm labor and fertilizer application. These inputs can respond to the observed weather in a particular year, analogous to the variable input L in the stylized example. In order to distinguish between the responses to growing season conditions and responses to changes in relative prices, we include prices for two outputs (off-farm work and maize) and three inputs (improved seed, fertilizer, and hired labor). We do not include prices for ordinary maize seed because the vast majority of farmers don't participate in that market, but instead save their own seed from the previous year. In contrast to variable inputs like fertilizer and labor, the allocation of land to improved maize varieties is a decision made at the start of the growing season and cannot be easily adjusted in the event of an unexpected weather pattern. Since planting area is not necessarily optimized for growing season weather in past observations, making impact assessments based on this suboptimal behavior will bias the estimates. The choice of improved maize share is analogous to the fixed input K in the stylized example, where $\overline{K}$ does not respond at all to P. Since allowing greater flexibility in input use improves the reliability of the estimate, we predict *optimal* improved maize share separately (in stage one) conditional on weather history, prices and socio-demographic factors and include this predicted value (rather than the observed value) in the profit equation. In doing so, we effectively replace $\overline{K}$ with K' (in π_2) by explicitly modeling the fact that improved maize share can be adjusted as climate change sets in.

Other inputs in the profit equation include the two weather variables, cumulative growing season heat and cumulative growing season precipitation (both used in DG's analysis). Measuring temperature according to degree-days is more reliable than using monthly means because the former better captures the non-linear effects of temperature on crop performance. Finally, we control for the effect of assets on annual net income by including the value of durable goods and livestock owned (z_4) and total landholding (z_5). The ownership of durable goods and livestock is likely to increase the household's earning potential and enhance their ability to cope with unexpected weather conditions (Di Falco et al., 2011). Thomas et al. (2007) found that livestock act as a safety net for farmers in South Africa tend to shift their attention toward livestock when droughts occur. Both landholding and assets influence a household's earning capacity and food security.

Because we do not know the specific structure of (5) in advance, we model profit as a translog function of prices and fixed inputs so as to allow for flexibility in the particular form. We choose p_y to be the numeraire and normalize profit and all other prices by p_y.

(8)

$$\ln \pi' = \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln p_i' + \frac{1}{2}\sum_{i=1}^{4}\sum_{h=1}^{4} \gamma_{ih} \ln p_i' \ln p_h' + \sum_{i=i}^{4}\sum_{k=1}^{5} \delta_{ik} \ln p_i' \ln z_k + \sum_{k=1}^{5} \theta_k \ln z_k$$
$$+ \frac{1}{2}\sum_{k=1}^{5}\sum_{j=1}^{5} \phi_{kj} \ln z_k \ln z_j$$

where π' denotes normalized profit and p_i' denotes normalized prices for i = 1, 2, 3, 4. We impose symmetry by forcing $\gamma_{ih} = \gamma_{hi}$ for all i and h. We derive the i^{th} input demand (or output supply) equation by differentiating (8) with respect to $\ln p_i'$. The equality on the far left-hand side of (9) follows from Hotelling's Lemma.

(9) $$x_i^* \frac{p_i'}{\pi'} = \frac{\partial \pi'}{\partial p_i'}\frac{p_i'}{\pi'} = \frac{\frac{\partial \pi'}{\pi'}}{\frac{\partial p_i'}{p_i'}} = \begin{cases} \dfrac{\partial \ln \pi'}{\partial \ln p_i'} & if\ p_i\ is\ an\ output\ price \\ -\dfrac{\partial \ln \pi'}{\partial \ln p_i'} & if\ p_i\ is\ an\ input\ price \end{cases}$$

Each input demand and output supply is expressed as a share of total profit in (10) – (13). These equations are derived from (8) as follows:

(10) $$x_1^* \frac{p_1'}{\pi'} = \frac{\partial \ln \pi'}{\partial \ln p_1'} = \alpha_1 + \sum_{i=1}^{4} \gamma_{1i} \ln p_i' + \sum_{k=1}^{5} \delta_{1k} \ln z_k$$

(11) $$-x_2^* \frac{p_2'}{\pi'} = \frac{\partial \ln \pi'}{\partial \ln p_2'} = \alpha_2 + \sum_{i=1}^{4} \gamma_{2i} \ln p_i' + \sum_{k=1}^{5} \delta_{2k} \ln z_k$$

(12) $$-x_3^* \frac{p_3'}{\pi'} = \frac{\partial \ln \pi'}{\partial \ln p_3'} = \alpha_3 + \sum_{i=1}^{4} \gamma_{3i} \ln p_i' + \sum_{k=1}^{5} \delta_{3k} \ln z_k$$

We estimate the parameters in (8) and (10) – (12) using a seemingly unrelated regression.

Share of Household Income Earned Off-Farm

Since we are interested in how the allocation of time toward off-farm work responds to climate, we derive the supply function for this output y. Since the profit shares sum to 1 by definition, the share of off-farm labor income is given by

(13) $$y^* \frac{p_y}{\pi^*} = (1 - \frac{p_1 x_1^*}{\pi^*} + \frac{p_2 x_2^*}{\pi^*} + \frac{p_3 x_3^*}{\pi^*} + \frac{p_4 x_4^*}{\pi^*}).$$

Thus, the supply function for off-farm labor is

(14) $$y^* = \pi'(1 - \frac{p_1 x_1^*}{\pi^*} + \frac{p_2 x_2^*}{\pi^*} + \frac{p_3 x_3^*}{\pi^*} + \frac{p_4 x_4^*}{\pi^*}).$$

To determine the elasticity of off-farm labor supply with respect to growing season precipitation we first take the natural logarithm of both sides of (14).

(15) $$\ln y^* = \ln \pi' + \ln\left(1 - \frac{p_1 x_1^*}{\pi^*} + \frac{p_2 x_2^*}{\pi^*} + \frac{p_3 x_3^*}{\pi^*} + \frac{p_4 x_4^*}{\pi^*}\right)$$

Differentiating (15) with respect to $\ln z_3$ yields

(16) $$\frac{\partial \ln y^*}{\partial \ln z_3} = \frac{\partial \ln \pi'}{\partial \ln z_3} + \frac{\partial \ln\left(1 - \frac{p_1 x_1^*}{\pi^*} + \frac{p_2 x_2^*}{\pi^*} + \frac{p_3 x_3^*}{\pi^*} + \frac{p_4 x_4^*}{\pi^*}\right)}{\partial \ln z_3}.$$

In terms of parameters, this becomes

(17)

$$\frac{\partial \ln y^*}{\partial \ln z_3} = \sum_{i=1}^{4} \delta_{i3} \ln p_i' + \theta_3 + \sum_{j=1}^{5} \phi_{j3} \ln z_3 - \sum_{i=1}^{4} \delta_{i3} \Big/ \left(1 - \frac{p_1 x_1^*}{\pi^*} + \frac{p_2 x_2^*}{\pi^*} + \frac{p_3 x_3^*}{\pi^*} + \frac{p_4 x_4^*}{\pi^*}\right)$$

Evaluating $p_i x_i^*/\pi^*$ at their sample means results in a quantity that depends only on parameters, initial price and precipitation levels and average profit shares. Let $\overline{S_i}$ denote the average profit share accounted for by input or output i among the sample of households.

(18)

$$\frac{\partial \ln y^*}{\partial \ln z_3} = \sum_{i=1}^{4} \delta_{i3} \ln p_i' + \theta_3 + \sum_{j=1}^{5} \phi_{j3} \ln z_3 - \sum_{i=1}^{4} \delta_{i3} / (1 - \bar{S}_1 + \bar{S}_2 + \bar{S}_3 + \bar{S}_4)$$

Once these parameters have been estimated, (18) can be used to simulate the response of off-farm labor supply to a change in total growing season precipitation. As climate becomes more variable, we would expect farmers to diversify their income across on-farm and off-farm sources.

Analysis of Climate Change Impacts

The overall impact of climate change on profit is found by taking the derivative of $\ln \pi'$ with respect to the natural log of the two climate variables z_2 and z_3. This gives the proportional change in profit per proportional change in cumulative growing season rainfall and monthly variability, respectively.

(19)

$$\frac{\partial \ln \pi'}{\partial \ln z_2} = \frac{\frac{\partial \pi'}{\pi'}}{\frac{\partial z_2}{z_2}} = \sum_{i=1}^{4} \delta_{i2} \ln p_i' + \theta_2 + \phi_{12} \ln z_1 + \sum_{k=2}^{5} \phi_{k2} \ln z_k$$

(20)

$$\frac{\partial \ln \pi'}{\partial \ln z_3} = \frac{\frac{\partial \pi'}{\pi'}}{\frac{\partial z_3}{z_3}} = \sum_{i=1}^{4} \delta_{i3} \ln p_i' + \theta_3 + \phi_{13} \ln z_1 + \sum_{k=2}^{5} \phi_{k3} \ln z_k$$

We hypothesize that the overall sign of (19) will be negative as higher growing season temperature places greater stress on crops and reduces yields, though we expect the sign of (20) to be positive as yield should be enhanced by a rainier growing season. Note that hybrid maize share, z_1, has been removed from summation on the right-hand side to highlight its role in shaping the relationship between profit and climate. This parameter is central to our research question, namely how does the share of land planted with improved maize varieties influence the impact of climate on profit? We hypothesize that while (19) ought to be less than zero overall, the sign of ϕ_{12} should be positive since it ought to lessen the harsh effects of temperature on yield. In turn, we expect a negative sign for ϕ_{13}—a higher share of land planted with improved maize varieties ought to diminish the loss that results from a decrease in rainfall.

Recall that in (12) z_1 is a fixed input, implying that the derivatives of profit with respect to cumulative growing season rainfall and variability ordinarily would not account for adjustments in improved maize share. However, because z_1 itself is a function of climate (as modeled in stage one), we must employ the chain rule to get the total derivative of profit with respect to climate. This total derivative can then be used to simulate the welfare impact of climate change as it is translated through the household's behavioral response (adjusting improved maize share).

For clarity, we group the terms in (12) that do not include z_1 on the left and those that do include z_1 on the right, explicitly writing z_1 as a function of the stage one variables.

(21)

$$\ln \pi' = \left\{ \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln p_i' + \frac{1}{2}\sum_{i=1}^{4}\sum_{h=1}^{4} \gamma_{ih} \ln p_i' \ln p_h' + \sum_{i=i}^{4}\sum_{k=2}^{5} \delta_{ik} \ln p_i' \ln z_k + \sum_{k=2}^{5} \theta_k \ln z_k + \frac{1}{2}\sum_{k=2}^{5}\sum_{j=2}^{5} \phi_{kj} \ln z_k \ln z_j \right\}$$

$$+ \left\{ \sum_{i=1}^{4} \delta_{i1} \ln p_i' \ln z_1(w_1, w_2, \dots, w_{14}) + \theta_1 \ln z_1(w_1, w_2, \dots, w_{14}) + \frac{1}{2}\phi_{11}[\ln z_1(w_1, w_2, \dots, w_{14})]^2 + \sum_{k=2}^{5} \phi_{1k} [\ln z_1(w_1, w_2, \dots, w_{14})] \ln z_k \right\}$$

The terms in the left-hand brackets correspond to climate's direct effect on profit, while those in the right-hand brackets represent its indirect effect on profit through the household's adjustment of improved maize share. Note that our measures of climate w_1 and w_2 are thirty-year means of cumulative growing season heat and precipitation, while the variables in the household net income equation, z_2 and z_3, measure weather conditions in a particular year. This could be troublesome when trying to link improved maize share to the weather variables z_2 and z_3; however, in terms of future projections, the conditions in any given year are informed by the underlying climate, so the expected values of z_2 and z_3 are w_2 and w_3, respectively. If in fifty years, the mean of cumulative growing season degree-days is projected to increase by Δw_2, then we expect improved maize share to adjust by the amount specified in the stage one estimation. Meanwhile, we expect Δz_2 between that future year and the present to equal Δw_2, the change in mean temperature.

(22)

$$\ln \pi' = \left\{ \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln p_i' + \frac{1}{2} \sum_{i=1}^{4} \sum_{h=1}^{4} \gamma_{ih} \ln p_i' \ln p_h' + \sum_{i=i}^{4} \sum_{k=2}^{5} \delta_{ik} \ln p_i' \ln z_k + \sum_{k=2}^{5} \theta_k \ln z_k \right.$$
$$\left. + \frac{1}{2} \sum_{k=2}^{5} \sum_{j=2}^{5} \phi_{kj} \ln z_k \ln z_j \right\}$$
$$+ \left\{ \sum_{i=1}^{4} \delta_{i1} \ln p_i' \ln z_1(z_2, z_3) + \theta_1 \ln z_1(z_2, z_3) + \frac{1}{2} \phi_{11} [\ln z_1(z_2, z_3)]^2 \right.$$
$$\left. + \sum_{k=2}^{5} \phi_{1k} [\ln z_1(z_2, z_3)] \ln z_k \right\}$$

Using this equivalence of long-run mean conditions and the expected conditions in a particular year, we arrive at (22) by replacing w_2 and w_3 with z_2 and z_3 and differentiate (22) respect to $\ln z_2$ and $\ln z_3$ to estimate the effects of climate on profit through adaptation along with the direct climate change effects. This results in a special case of the general framework introduced in (3). The derivatives of the terms in the left-hand brackets will be the same as in (19) and (20), but the terms on the right where $z_1(z_2, z_3)$ appears must be differentiated using the chain rule.

(23)

$$\frac{\partial \ln \pi'}{\partial \ln z_2} = \left\{\sum_{i=1}^{4} \delta_{i2} \ln p_i' + \theta_2 + \sum_{k=2}^{5} \phi_{k2} \ln z_k\right\}$$

$$+ \left\{\sum_{i=1}^{4} \delta_{i1} ln\, p_i' \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_2}{z_2}\right]} + \theta_1 \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_2}{z_2}\right]} + \phi_{11}[\ln z_1(z_2,z_3)] \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_2}{z_2}\right]}\right.$$

$$\left. + \phi_{12}\left(\frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_2}{z_2}\right]} \ln z_2 + \ln z_1(z_2,z_3)\right) + \sum_{k=3}^{5} \phi_{1k} \ln z_k \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_2}{z_2}\right]}\right\}$$

(24)

$$\frac{\partial \ln \pi'}{\partial \ln z_3} = \left\{\sum_{i=1}^{4} \delta_{i3} \ln p_i' + \theta_3 + \sum_{k=2}^{5} \phi_{k3} \ln z_k\right\}$$

$$+ \left\{\sum_{i=1}^{4} \delta_{i1} ln\, p_i' \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]} + \theta_1 \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]} + \phi_{11}[\ln z_1(z_2,z_3)] \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]}\right.$$

$$+ \phi_{12} \ln z_2 \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]} + \phi_{13}\left(\frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]} \ln z_3 + \ln z_1(z_2,z_3)\right)$$

$$\left. + \sum_{k=4}^{5} \phi_{1k} \ln z_k \frac{\left[\frac{\partial z_1(z_2,z_3)}{z_1(z_2,z_3)}\right]}{\left[\frac{\partial z_3}{z_3}\right]}\right\}$$

The output of the stage one and stage two estimations is assembled as specified in (23) and (24) to model the relationships between climate, improved maize share and net household income. This framework provides one way of answering our central research question, namely, to what extent do households in Malawi adapt to climate change and what are the welfare implications of those changes? As in (19) and (20), we expect climate change (increased temperature, reduced precipitation) to impact profit negatively through the direct effects in the left-hand brackets; however, this negative impact should be partially offset by the terms in the right-hand brackets, where climate's effect on profit is channeled through its effect on improved maize share.

Results

Improved Maize Adoption

Results indicate that the share of cultivated land planted with improved maize seed varieties responds to historical precipitation variability. We measure both variability of monthly precipitation within the growing season as well as the variability of cumulative growing season rainfall across years, finding each to be significant predictors of the intensity of improved maize use (see Table 3). Cumulative growing season precipitation was not determined to significantly affect share of land allocated to improved maize across most specifications, though it was found significant when precipitation history was adjusted for the age of the household head (that is, older household heads were assumed to view the full historical precipitation record dating back to 1980, while this record was truncated prior to age 16 for younger household heads). The relationship between rainfall variability and improved maize share appears to be non-linear as the coefficients on both the linear and squared terms are statistically significant. Both improved seed price and fertilizer price are negatively correlated with improved maize share, as expected. Improved maize share is related positively to the value of livestock and durable goods owned, though this parameter falls beneath the significance threshold. Receipt of useful advice on the use of improved seed varieties appears to have a positive and significant impact on improved maize share.

Climate Change Impacts

We combine the parameter estimates from the system of profit, input demand, and output supply equations to construct the partial effect of climate on net household income. As presented in equations (20) and (21), we compute separate effects for mean growing season rainfall and monthly rainfall variation within the growing season. Furthermore, using stage one to predict optimal improved maize share given the particular growing season conditions, we can compare climate change impacts with and without this adaptation strategy. In this way, we quantify the welfare effects associated with this behavior. Taking the statistically significant parameters from Table 4 and evaluating the exogenous variables at their means yields the elasticities of household profit with respect to mean and variation of growing season rainfall found in Table 5. We estimate that household profit decreases by almost 19% for every 1% decrease in total growing season precipitation. Since the coefficients on mean precipitation in stage one were insignificant, we do not expect an adjustment of improved maize share in response to this shift. In terms of variability, we expect household income to fall one and a half percent for a one percent increase in the coefficient of variation for monthly rainfall within the growing season. Since this intra-seasonal variability was determined to be statistically significant in stage one, we account for the expected shift in improved maize share induced by the change in rainfall variability. Letting the household reallocate land to improved maize varieties reduces this elasticity (in absolute value) to -1.3%. In this way, we uncover statistically significant benefits associated with the ability to shift the allocation of land toward improved maize varieties, though the magnitude is relatively small.

Di Falco et al. (2011), in their study of climate change adaptation in Ethiopia, find households that adapted produced about 20% more than if they had not adapted. Similarly, they estimate that non-adapting households could have increased incomes by 35% by undertaking an adaptation measure (common measures include changing crop varieties, adoption of soil and water conservation strategies, and tree planting). Our study corroborates this result, finding that increasing the adoption of improved maize partially offsets the damages associated with increased rainfall variability.

Apart from the role that improved maize varieties play in providing a buffer against increased precipitation variability, we also uncover statistically significant income gains associated with increasing the intensity of improved maize adoption. We estimate that a one percent increase in improved maize share results in a 1.7% increase in overall household income. Despite this significant income gain, we would not necessarily expect a complete shift to improved maize since local maize varieties are preferred for consumption purposes, thus the market for local maize remains prominent.

Table 3. Intensity of Improved Maize Adoption

share of cultivated land planted with improved maize varieties	Coefficient	p-value
value of livestock and durable goods	3.98E-08	0.126
growing season precipitation (23-29 yr history)	2.97E-04	0.343
" squared	2.37E-09	0.854
CV annual growing season precipitation (23-29 yr history)	-9.50***	0.004
" squared	27.2***	0.001
CV monthly growing season precip (within-year, 23-29 yr history)	-47.8***	0.000
" squared	30.6***	0.000
=1 if household experienced a bad weather shock in past 2 years	-0.017	0.224
previous year's maize price in kwacha per kg	0.0022244	0.207
fertilizer price	-9.98E-04***	0.000
qty of subsidized fertlizer acquired	2.05E-04*	0.079
off-farm wage rate, current year	-3.16E-05***	0.002
input loan	0.031	0.146
female head of household	-0.032	0.245
household size (adult equivalent)	0.002	0.718
landholding	-0.011	0.126
advice on new seed varieties	0.039**	0.031
improved maize seed price	-3.01E-04*	0.084
yr2003_04	-0.012	0.588
yr2007_08	0.122	0.000
yr2009_10	-0.050	0.373
constant	16.5	0.001

Table 4. Translog Profit Equation with Output Supply and Input Demand

log (household net income)	Coefficient	p-value
log(maize price)	1.926	0.532
log(fertilizer price)	-1.834	-0.589
log(labor price)	-0.502	-0.500
log(maize price)*log(maize price)	-0.010	0.889
log(maize price)*log(fertilizer price)	0.001	0.997
log(maize price)*log(labor price)	0.005	0.870
log(fertilizer price)*log(fertilizer price)	0.043	0.507
log(fertilizer price)*log(labor price)	0.014	0.699
log(labor price)*log(labor price)	-0.011	0.137
log(maize price)*log(improved maize share)	-0.026	0.197
log(maize price)*log(grw season precip)	-0.118	0.727
log(maize price)*log(cv grw season precip)	-0.402	0.113
log(maize price)*log(assets)	-0.037***	0.009
log(maize price)*log(landholding)	0.036	0.141
log(fertilizer price)*log(improved maize share)	0.020	0.317
log(fertilizer price)*log(grw season precip)	0.193	0.598
log(fertilizer price)*log(cv grw season precip)	0.412	0.150
log(fertilizer price)*log(assets)	0.050***	0.009
log(fertilizer price)*log(landholding)	-0.007	0.857
log(labor price)*log(improved maize share)	-0.004	0.755
log(labor price)*log(grw season precip)	0.056	0.475
log(labor price)*log(cv grw season precip)	-0.069	0.428
log(labor price)*log(assets)	-0.003	0.573
log(labor price)*log(landholding)	-0.006	0.365
log(improved maize share)	1.704*	0.058
log(grw season precip)	35.170**	0.046
log(cv grw season precip)	-3.501	0.765
log(assets)	-0.242	0.742
log(landholding)	1.197	0.309
log(improved maize share)*log(improved maize share)	0.006	0.409
log(improved maize share)*log(grw season precip)	-0.165*	0.096
log(improved maize share)*log(cv grw season precip)	0.157*	0.075
log(improved maize share)*log(assets)	-0.006	0.204
log(improved maize share)*log(landholding)	0.006	0.465
log(grw season precip)*log(grw season precip)	-1.917**	0.042
log(grw season precip)*log(cv grw season precip)	0.527	0.662
log(grw season precip)*log(assets)	0.039	0.613
log(grw season precip)*log(landholding)	-0.104	0.396
log(cv grw season precip)*log(cv grw season precip)	3.209***	0.001

log(cv grw season precip)*log(assets)	0.100	0.251
log(cv grw season precip)*log(landholding)	0.010	0.953
log(assets)*log(assets)	0.005	0.319
log(assets)*log(landholding)	-0.003	0.826
log(landholding)*log(landholding)	.023***	0.006
yr2003_04	-1.544	0.611
yr2006_07	-14.826**	0.023
yr2008_09	-14.316***	0.000
log(maize price)*yr2003_04	-0.023	0.747
log(maize price)*yr2006_07	0.230**	0.062
log(maize price)*yr2008_09	-0.053	0.446
log(fertilizer price)*yr2003_04	-0.113	0.244
log(fertilizer price)*yr2006_07	-0.240	0.125
log(fertilizer price)*yr2008_09	-0.073	0.424
log(labor price)*yr2003_04	-0.016	0.422
log(labor price)*yr2006_07	-0.018	0.601
log(labor price)*yr2008_09	-0.003	0.870
log(improved maize share)*yr2003_04	-0.001	0.948
log(improved maize share)*yr2006_07	0.006	0.894
log(improved maize share)*yr2008_09	-0.033	0.154
log(grw season precip)*yr2003_04	0.180	0.582
log(grw season precip)*yr2006_07	1.587**	0.020
log(grw season precip)*yr2008_09	1.543***	0.000
log(cv grw season precip)*yr2003_04	0.095	0.884
log(cv grw season precip)*yr2006_07	-1.133*	0.060
log(cv grw season preicp)*yr2008_09	-.797**	0.043
log(assets)*yr2003_04	-0.016	0.623
log(assets)*yr2006_07	-.088**	0.034
log(assets)*yr2008_09	-.049*	0.081
log(landholding)*y2003_04	0.018	0.715
log(landholding)*yr2006_07	0.236***	0.005
log(landholding)*yr2008_09	0.002	0.980
maize output supply		
log(maize price)	-0.019	0.889
log(fertilizer price)	0.001	0.997
log(labor price)	0.005	0.870
log(improved maize share)	-0.026	0.197
log(grw season precip)	-0.118	0.727
log(cv grw season precip)	-0.402	0.113
log(assets)	-0.037***	0.009
log(landholding)	0.036	0.141

yr2003_04	-0.023	0.747
yr2006_07	0.230*	0.062
yr2008_09	-0.053	0.446
fertilizer input demand		
log(maize price)	-0.001	0.997
log(fertilizer price)	0.087	0.507
log(labor price)	0.014	0.699
log(improved maize share)	0.020	0.317
log(grw season precip)	0.193	0.598
log(cv grw season precip)	0.412	0.150
log(assets)	.050***	0.009
log(landholding)	-0.007	0.857
yr2003_04	-0.113	0.244
yr2006_07	-0.240	0.125
yr2008_09	-0.073	0.424
labor input demand		
log(maize price)	0.005	0.870
log(fertilizer price)	0.014	0.699
log(labor price)	-0.023	0.137
log(improved maize share)	-0.004	0.755
log(grw season precip)	0.056	0.475
log(cv grw season precip)	-0.069	0.428
log(assets)	-0.003	0.573
log(landholding)	-0.006	0.365
yr2003_04	-0.016	0.422
yr2006_07	-0.018	0.601
yr2008_09	-0.003	0.870

Table 5. Elasticity of Net Household Income With Respect to Climate (with/without adaptation)

	without expected adjustment	with expected adjustment
mean growing season precipitation	18.94	---
monthly growing season precipitation variability	-1.55	-1.31

Share of Income Earned Off-Farm

We plug the parameter estimates from Table 4 into equation (19) to generate the elasticity of off-farm income with respect to the mean and variation of growing season precipitation. The important parameters that would reveal a change in the household's input or output mix with respect to weather variation are the coefficients on interactions between prices and weather variables. This includes the group of terms on the right-hand side of (19). We find none of these coefficients to be statistically significant. The remaining terms in (19) are simply the derivative of profit with respect to climate shown in Table 5. In this way, our model predicts that the supply of off-farm labor (as would be the case for all inputs and outputs) will shift in exactly the same proportion as the change in profit.

Conclusion

In our sample of Malawi households, we uncover statistically significant relationships between precipitation history and the share of cultivated land planted with improved maize varieties. Specifically, the variability of growing season precipitation both across years and within the growing season appear to have an impact on this planting decision. Combining this result with a household profit equation, we compute the elasticity of profit with respect to mean growing precipitation and intra-seasonal precipitation variability both with and without the expected adjustment in improved maize share dictated by this stage one model. We find household profit to be highly responsive to mean growing season precipitation, though we do not expect any adjustment to a shift in mean rainfall given the insignificance of this variable in the first stage estimation. We uncover significant negative impacts associated with the variability of precipitation within the growing season and determine that the expected adjustment in improved maize share offsets a small fraction of these losses. We estimate that incomes fall by 1.5% for every 1% increase in the coefficient of variation of monthly growing season precipitation Given that the percentage loss in income with respect to a percent increase in variability exceeds one even when we account for the adjustment in improved maize share, the expected costs of climate change incurred by Malawi farmers appear to be substantial.

References

Adams, R.M., B.A. McCarl, D.J. Dudek and J.D. Glyer. 1988. "Implications of Global Climate Change for Western Agriculture," *Western Journal of Agricultural Economics* 13:2, 348-356.

Amaza, P., K. Ayuba, and A. Kamara. 2008. Farmers' Perception, Profitability and Factors Influencing the Adoption of Improved Maize Varieties in the Guinea Savannas of Nigeria. Conference on International Research on Food Security, Natural Resource Management and Rural Development, University of Hohenheim, October 7-9.

Apata, T.G., K.D. Samuel and A.O. Adeola. 2009. Analysis of Climate Change Perception and Adaptation among Arable Food Crop Farmers in South Western Nigeria. Contributed Paper prepared for presentation at the International Association of Agricultural Economists' 2009 Conference, Beijing, China, August 16-22.

Bayard, B., C.M. Jolly, and D.A. Shannon. 2007. The economics of adoption and management of alley cropping in Haiti. *Journal of Environmental Management* 84(1): 62-70.

Bellon, M.R. and J. Risopoulos. 2001. Small-Scale Farmers Expand the Benefits of Improved Maize Germplasm: A Case Study from Chiapas, Mexico. *World Development* 29(5): 799-811.

Below, T., A. Artner, R. Siebert and S. Sieber. 2010. Micro-level Practices to Adapt to Climate Change for African Small-scale Farmers. IFPRI Discussion Paper 00953.

Bryan, E., T.T. Deressa, G.A. Gbetibouo and C. Ringler. 2009. Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science and Policy* 12: 413-426.

Daberkow, S.G. and W.D. McBride. 2003. Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US. *Precision Agriculture* 4: 163-177.

Deressa, Temesgen T., R.M. Hassan, C. Ringler, T. Alemu and M. Yesuf. 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change* 19:248-255.

Deressa, T.T., C. Ringler and R.M. Hassan. 2010. Factors Affecting the Choices of Coping Strategies for Climate Extremes. IFPRI Discussion Paper 01032.

Deressa, T.T., R.M. Hassan and C. Ringler. 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science* 149: 23-31.

Desanker, Paul, and Christopher Magadza. 2001. Africa. In *Climate Change 2001: Impacts, Adaptation and Vulnerability*, edited by I.P.o.C. Change. Geneva: IPCC.

Deschenes, O. and M. Greenstone. 2007. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review* 97: 354 -385.

Di Falco, S., M. Veronesi, and M. Yesuf. 2011a. Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics* 93(2): 1-18.

Di Falco, S., M. Yesuf, G. Kohlin and C. Ringler. 2011b. Estimating the Impact of Climate Change on Agriculture in Low-Income Countries: Household Level Evidence from the Nile Basin, Ethiopia. *Environmental and Resource Economics* 52: 457-478.

Di Falco, S. and M. Veronesi, 2012. "How African Agriculture Can Adapt to Climate Change? A Counterfactual Analysis from Ethiopia." Working Paper Series, Department of Economics, University of Verona No. 14.

Easterling, W.E., N.J. Rosenberg, K.M. Lemon and M.S. McKenney. 1992a. "Simulation of crop responses to climate change: effects with present technology and no adjustments (the 'dumb farmer' scenario)," *Agricultural and Forest Meteorology* 59:53-73.

Easterling, W.E., N.J. Rosenberg, K.M. Lemon and M.S. McKenney. 1992b. "Simulation of crop responses to climate change: effects with present technology and currently available adjustments (the 'smart farmer' scenario)," *Agricultural and Forest Meteorology* 59:75-102.

Etoundi, S.M.N. and B.K. Dia. 2008. Determinants of the adoption of improved varieties of Maize in Cameroon: case of CMS 8704. *Proceedings of the African Economic Conference 2008*, 397-413.

Feleke, S. and T. Zegeye. 2006. Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy* 31: 442-457.

Feder, G., R.E. Just, and D. Zilberman. 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change* 33(2): 255-298.

Fosu-Mensah, B.Y., P.L.G. Vlek and D.S. MacCarthy. 2012. Farmer's perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. *Environment Development and Sustainability* 14: 495-5.

Gbetibouo, G.A., R. Hassan and C. Ringler. 2010. Modeling Farmers' Adaptation Strategies for Climate Change and Variability: The Case of The Limpopo Basin, South Africa. *Agricultural Economics Research, Policy and Practice in Southern Africa*. 49: 217-234.

Guiteras, R. 2009. The Impact of Climate Change on Indian Agriculture. Job Market Paper. Unpublished.

Hassan, R. and C. Nhemachena. 2008. "Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis," *African Journal of Agricultural and Resource Economics* 2:83-104

IPCC, 2007: *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 976pp.

Kaliba, A., H. Verkuijl and W. Mwangi. 2000. Factors Affecting Adoption of Improved Maize Seeds and Use of Inorganic Fertilizer for Maize Production in the Intermediate and Lowland Zones of Tanzania. *Journal of Agricultural and Applied Economics* 32(1):35-47.

Langyintuo, A.S. and M. Mekuria. 2008. Assessing the influence of neighborhood effects on the adoption of improved agricultural technologies in developing agriculture. *African Journal of Agricultural and Resource Economics* 2(2): 151-169.

Langyintuo, A.S. and C. Mungoma. 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy* 33(6): 550-559.

Lobell, D., M. Banziger, C. Magorokosho, and B. Vivek. 2011. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change* 1: 42-45.

Maddison, D. 2007. The perception of and adapation to climate change in Africa. *World Bank Policy Research Working Paper*, 4308. The World Bank, Washington, DC.

Molua, Ernest L. 2002. Climate Variability, Vulnerability and Effectiveness of Farm-Level Adaptation Options: the Challenges and Implications for Food Security in Southwestern Cameroon. *Environment and Development Economics* 7 3, 2002): 529-545

Molua, Ernest L. 2011. "Climate change and African agriculture: Review of impact and adaptation choices," Chapter 10 in *Africa in Focus: Governance in the 21st Century* (eds.) Kwandiwe Kondlo and Chinenyengozi Ejiogu. HSRC Press.

Morris, M.L., R. Tripp, and A.A. Dankyi. 1999. *Adoption and Impacts of Improved Maize Production Technology: A Case Study of the Ghana Grains Development Project*. Economics Program Paper 99-01. Mexico, D.F.: CIMMYT.

Mutekwa, V.T. 2009. "Climate Change Impacts and Adaptation in the Agricultural Sector; The Case of Smallholder Farmers in Zimbabwe." *Journal of Sustainable Development in Africa* 11(2): 237-256.

Mwabu, G., W. Mwangi, and H. Nyangito. 2006. Does Adoption of Improved Maize Varieties Reduce Poverty? Evidence from Kenya. Poster paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18.

Parry, M.L., C. Rosenzweig, A. Iglesias, "Agriculture," in Feenstra, J.F., Burton, I., Smith, J.B., Tol, R.S.J. (eds.): 1998, *Handbook on Methods for Climate Change Impact Assessment and Adaptation Strategies*. UNEP/Vrije Universitcit Institute for Environmental Studies, Amsterdam.

Pauw, K. J. Thurlow and D. van Seventer. 2010. Droughts and floods in Malawi: Assessing the economywide effects. IFPRI Discussion Paper 00962.

Paudel, P. and A. Matsuoka. 2008. Factors Influencing Adoption of Improved Maize Varieties in Nepal: A Case Study of Chitwan District. *Australian Journal of Basic and Applied Sciences* 2(4): 823 -834.

Rosenzweig, C. and M.L. Parry 1994. Potential impact of climate change on world food supply. *Nature* 367: 133-138.

Sanghi, A. and R. Mendelsohn. 2008. “The impacts of global warming on farmers in Brazil and India,” *Global Environmental Change*, 18:4 655-665.

Schlenker, W., W. Michael Hanemann and Anthony C. Fisher. 2005. “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach.” *American Economic Review*, 95(1):395-406.

Schlenker, W. and D. Lobell. 2010. Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*. 5 014010.

Silvestri, S., E. Bryan, C. Ringler, M. Herrero and B. Okoba. 2012. Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change* 12(4): 791 -802

Smit, B. and O. Pilofosova. 2001. Adaptation to Climate Change in the Context of Sustainable Development and Equity. In *Climate Change 2001: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Third Assessment of The Intergovernmental Panel on Climate Change*, Eds. J.J. McCarthy, O.F. Canziani, N.A.Leary, D.J Dokken, K.S. White., Cambridge University Press, Cambridge, UK, 717- 74.

Sserunkuuma, D. 2005. The Adoption and Impact of Improved Maize and Land Management Technologies in Uganda. *Electronic Journal of Agricultural and Development Economics* 2(1): 67-84

Thomas D.S.G., C. Ywyman, H. Osbahr and B. Hewitson. 2007. “Adaptation to climate change and variability: farmer responses to intro-seasonal precipitation trends in South Africa.” *Climatic Change*. 83: 301-322.

Wang, J. Mendelsohn, R., Dinar, A., Huang. J., Rozelle, S. and Zhang, L. 2009. The impact of climate change on China’s agriculture. *Agricultural Economics* 40: 323-337.

World Bank. 2007. *Malawi Poverty and Vulnerability Assessment: Investing in our Future.* Washington, DC: World Bank.