

Household Resilience to Drought: The Case of Salima District in Malawi

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ABSTRACT

This study identifies factors that affect resilience to drought among smallholder farmers in Salima, one of the districts frequently affected by drought in Malawi. The study contributes to the existing literature by constructing a drought resilience index (DRI) and uses it to determine the effect of drought resilience on the welfare of farming households. Principal Components Analysis (PCA) is used to construct the DRI. Appreciating that smallholder farmers actively respond to events that threaten their livelihoods, the study identified how factors such as household assets, social capital, the size of land held by the farming household, and others factors help farmers to absorb adverse welfare effects resulting from prolonged dry spells and droughts. In order to capture the effect of drought on the welfare of farming households, a stochastic frontier production function is estimated. Results suggest that over 62 percent of households in the study area were not resilient and, hence, vulnerable to the adverse effects of dry spells. Factors such as age of the household head, size of the farm family, landholding size, and the number of immediate family members living outside the household are identified as affecting the drought resilience of farming households. The study also finds a positive correlation between resilience and improved household welfare. The policy implications from the results of this study include promoting productivity enhancing technologies, diversifying crop production from maize, and pursuing household livelihoods outside of agriculture in order to reduce the risks to household welfare resulting from drought.

Keywords: Drought, vulnerability, resilience, livelihood, welfare.

I. INTRODUCTION

Dry spells and droughts are known to contribute adversely to the livelihoods and welfare of many people in developing countries. In Malawi, over 85 percent of the population lives in rural areas and depends on natural resources for their livelihoods – soil, water, fisheries from inland lakes, and fuelwood from forests (Lunduka et al. 2010). The country frequently experiences adverse climatic conditions, which negatively affects the use of natural resources by rural households and, consequently, the livelihoods and welfare of the many people that depend on those resources.

Malawi is prone to natural and human induced shocks. Fifteen out of the 28 districts of the country are prone to different natural and human induced hazards, based on historical data and the climatology of the country (Phiri 2010). The Lower Shire Valley (districts of Nsanje, Chikwawa, and Mwanza) and districts along the shores of Lake Malawi (Mangochi, Salima, Nkhatakota, Nkhata Bay, and Karonga districts) are among those areas of the country particularly affected by dry spells, droughts, and floods. The incidence and intensity of these events have increased over the past two decades with negative consequences for food and water security, water quality, and the sustainability of livelihoods in rural communities (World Bank 2011). Almost every year, a significant number of people is affected by prolonged dry spells, drought, or floods in these areas. These disasters have resulted in loss of life, low agricultural output, with consequences on hunger and malnutrition, especially among children under five years of age; and disruption to industrial and other socio-economic activities.

These increasingly common weather-related shocks add to the many challenges that farmers face, ranging from declining soil fertility, increasing population, and rising prices of farm inputs, even as farm output prices remain low. Of all the sectors of the economy affected by these disasters, agriculture is the most severely affected. Prolonged dry spells, droughts, and floods present particularly problematic challenges because they are exogenous shocks that are beyond the influence of smallholder producers to prevent. For example, the Malawi Vulnerability Assessment Committee (MVAC) reported that about 9.5 percent of the Malawi population (approximately 1.1 million people) were food insecure between the months of October 2013 and March 2014. This was partly attributed to poor harvests that some parts of the country registered due to unfavourable weather conditions. It is therefore important for farmers to increase their resilience to the adverse effects of these shocks. If they become more resilient, they will be better able to deal with challenges that come their way without a significant loss in household welfare.

A number of studies have been conducted to determine how smallholder farmers have responded to some of the weather-related problems they face that affect their agricultural production and marketing (Matchaya 2007; Kankwamba et al. 2012). To our knowledge, no study has been specifically commissioned to study the resilience of farmers to dry spells and droughts in Salima district. This study was motivated by a desire to better understand the impacts of climatic change and variability on smallholder farmers in Malawi. These impacts are not evenly distributed across the population, with the people that are most vulnerable and exposed to the worst of such impacts being among those that are least able to cope with the associated risks (Adger, et al. 2003). The present study seeks to identify factors that affect resilience to drought among smallholder farmers in the Chipoka area of Salima district, which covers the area of Traditional Authorities Ndindi and Kambalame, and to determine the effect of such resilience on the welfare of the study households.

The study constructs a household-level drought resilience index and uses it to test two hypotheses. The first hypothesis is that a household's social-economic, demographic, community, and farm characteristics do not affect its resilience to drought, while the second is that drought resilience does not have any significant effect on the welfare of farming households.

Knowledge of the factors that affect resilience among smallholder farmers living in drought-prone areas would assist policy makers, non-governmental organisations (NGOs), and other stakeholders to formulate strategies and interventions that will enhance farmers' resilience to drought in the affected areas. Most studies that have been carried out have looked at regional and national losses that are incurred as a result of climate change. Most of the studies that have been conducted to calculate specific losses at district level have concentrated on districts in southern Malawi, such as Balaka, Nsanje, and Chikwawa (Phiri et al. 2012; Magombo et al. 2012). There have been few, if any, studies that have focused on the lakeshore districts of Malawi, especially to study factors that enhance resilience to the effects of drought among smallholder farmers. The present study also sets a model for similar research to be conducted in other parts of the country where farmers have also been negatively affected by drought.

The rest of the paper is as follows. After this introduction, a brief review of literature is provided. Thereafter, the study methodology is discussed, followed by results and discussion. A concluding section is provided that presents some policy implications of the study.

2. METHODS AND DATA SOURCES

2.1 Data and sampling

The study used a multi-stage sampling procedure to identify respondents for the study. Primary data were collected from smallholder maize producers in Salima district using a structured questionnaire. The sampling frame comprised a list of all twelve sections and thirty two villages from the study area. This list was obtained from the EPA offices at Chipoka. From the list, five sections were randomly selected and from these selected sections, twelve villages were randomly selected to participate in the study.

In order to determine the number of respondents needed for the study from each village, a probability-proportional-to-size (PPS) sampling technique was employed to come up with a sample of 427 respondents for the study. The sample size was determined using the following formula (Edriss 2003):

$$n = \frac{z^2}{e^2} \frac{p \cdot q \cdot N}{(N-1) + z^2 \cdot p \cdot q} \quad (1)$$

where n is the sample size to be determined and p is the proportion of farming households resilient to drought. This proportion is unknown, so a proportion of 0.5 was used. q is the proportion of farming households not resilient to drought. Since this proportion is also unknown, a proportion of 0.5 also was used. Z is the number of standard deviations at a given confidence level (i.e., 95 percent in this study), e is the acceptance error (0.05), and N is the population size (16,563 farming families). Substituting the values into the formula above yielded a sample size of 384. After adjusting for possible non-response among sample members, a sample size of 427 respondents was computed.

In addition to the quantitative survey, key informant interviews were used to provide explanations for some of the findings of the quantitative analysis.

2.2 Model for measuring drought resilience

Keil et al. (2006) indicate that, among other things, household risk management aims at smoothing consumption in the affected household. Therefore, resilience is measured as the observed degree of production and consumption of home-produced maize. To capture the effect of dry spells and droughts on consumption of home-produced food, an account was made on the absolute difference in expenditure on and consumption of selected food items between normal and drought situations. Keil et al. (2006) argue that "the share of expenditures relative to normal situations is expected to be positively correlated with household drought resilience." They also indicate that "differences in food consumption between normal and drought situations are expected to be negatively correlated to drought resilience in the case of superior foods and positive in the case of inferior foods." Accordingly, a household is considered to be fully resilient if all indicators remained unaffected under drought conditions.

2.2.1: ESTIMATING RESILIENCE OF A FARMING HOUSEHOLD

In order to identify a household as either resilient to drought or not, Principal Components Analysis (PCA), a multivariate analysis technique, was used to aggregate four production and consumption related indicators into the drought resilience index (DRI). Principal Component Analysis is a variable reduction technique that aims at reducing a large set of variables

into a smaller set of “artificial” variables called principal components. These principal components account for most of the variance in the original variables. Some authors have defined principal component analysis as a linear combination of optimally weighted observed variables (Holland 2008). In order for principal component analysis to work properly, a number of assumptions must be met. These assumptions include interval level measurement, random sampling, linear relationships between variables, and normality. In the present study, four variables are used in the principal component analysis. The selected variables are the amount of maize produced by smallholder farmers in a normal year without dry spells, the amount of maize produced in a bad year with a dry spell, the number of months a household consumes food produced by the household in a normal year, and the number of months a household consumes food produced by the household in a dry spell year.

Table 3.1 below shows descriptive statistics for these variables. It can be seen from the table that the average amount of maize produced by a farming household in a normal year is about 545 kilogrammes of maize per season for an average household comprised of about six members. This translates to about eleven 50 kg bags per farming household. The large standard deviation of 453 indicates significant variability in the amount of maize produced. Similar trends can be seen in the other three variables used in the analysis.

Table 2.1: Descriptive statistics for variables used in constructing the drought resilience index

Variable	Mean	Standard deviation
Maize production in a normal year, kg	545.0	453.49
Maize production in year with dry spells, kg	284.5	276.86
Number of months household consumed household-produced maize in normal year	8.5	2.81
Number of months household consumed household-produced maize in year with dry spells	4.6	2.65

Source: Author’s computations from study survey. 427 observations.

It is important to bear in mind that the 2013/14 farming season was generally a good year for maize production in the study area, as there were no significant reported cases of dry spells in the area. Farmers made reference to the 2011/12 and 2012/13 farming seasons to provide responses regarding the effects of dry spells on their farm production.

The four indicators were aggregated into a drought resilience index using the formula:

$$DRI = w_n p_n + w_d p_d + w_{cn} m_n + w_{cd} m_d \quad (2)$$

DRI represents the drought resilience index. *w* represents weights derived from the component loadings from the first principal components. The data from which the components were derived was standardized to have a zero mean and unit variance. Accordingly, $w_n p_n$ represents the weight for maize production in a normal year multiplied by the actual amount of maize produced in a good year; $w_d p_d$ represents the weight for maize production in a drought year multiplied by the actual amount of maize produced in a drought year; $w_{cn} m_n$ represents the weight for the number of months a household remains with household-produced food multiplied by the number of months the household consumes household-produced food in a normal year, and $w_{cd} m_d$ represents the weight for the number of months a household remains with household-produced food during a drought year multiplied by the actual number of months a household remains with household-produced food in a drought year. All variables are expected to correlate positively with drought resilience. This is because an increase in any one of the variables was expected to be associated with an improvement in the well-being of the farming household.

2.2.2: MODEL FOR DETERMINANTS OF HOUSEHOLD RESILIENCE TO DRY SPELLS AND DROUGHT

In order to test the first hypothesis that a household’s social-economic, demographic, community, and farm characteristics do not affect its resilience to drought, a probit regression procedure was used to identify factors that determine resilience among farming households in the study area. The drought resilience index, which was generated using principal components analysis was used as a criteria for identifying a household as either resilient to drought or not. The probit regression model was considered to be the best model to apply on the available data in order to identify socioeconomic, demographic, community, and farm factors that affect the resilience of farming households. The model was chosen based on the findings of Tesso et al. (2012) who used the ordered probit regression model to analyze and identify determinants of household resilience to climate change induced shocks in North Shewa, Ethiopia. In this study we adopted a latent variable model (Long and Freese 2001). The model assumes a latent variable y^* that is in the range from $-\infty$ to $+\infty$ which is related to the observed independent variables, x , by the following structural equation:

$$y_i^* = x_i \beta + \varepsilon_i \quad (3)$$

where i indicates the observation; β represents parameters to be estimated, and ε represents the random disturbance term. For a single explanatory variable, the notation can be simplified to;

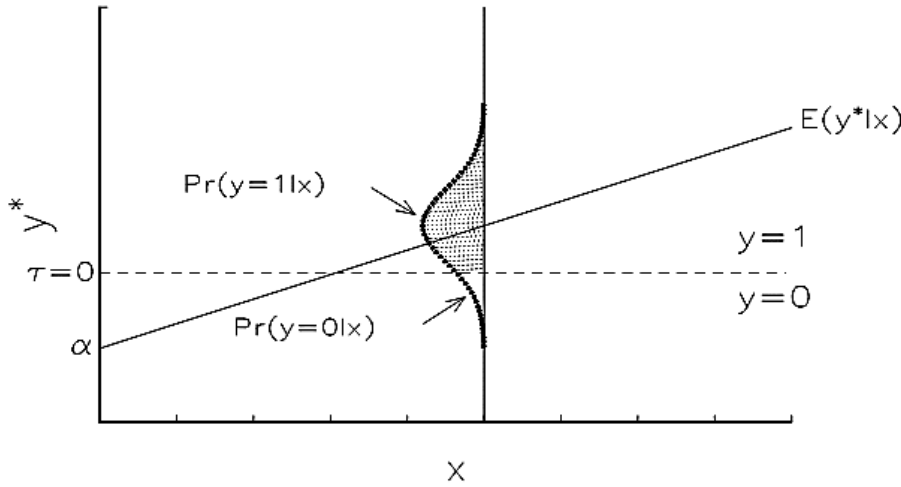
$$y_i^* = \alpha + \beta_1 x + \varepsilon_i \quad (4)$$

The equations presented above are similar to linear regression equations with the important difference that the dependent variable is not observed (Long and Freese 2001). The link between the observed binary variable y and the latent variable y^* is made with a simple measurement equation:

$$y_i = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases} \quad (5)$$

where cases with $y^* > 0$ are observed as $y=1$, whereas cases with $y^* \leq 0$ are observed as $y=0$. The idea behind the latent variable is that it generates a tendency of behaving or responding in a particular way to a given situation. In this study the idea behind a latent variable is to be resilient against adverse effects resulting from dry spells and drought. While it is not possible to directly observe resilience to dry spells, a change in the latent variable is most likely to result in a change in observable characteristics. Figure 3.1 below shows the relationship between a latent variable y^* and the probability that a given observation possesses an attribute.

Figure 2.1: The relationship between a latent variable y^* and $\Pr(y=1)$



Source: Adapted from Long and Freese (2001).

From the figure above, it can be noted that;

$$\Pr(y = 1|x) = \Pr(y^* > 0|x) \quad (6)$$

Substituting the structural model and rearranging yields the following equation:

$$\Pr(y = 1|x) = \Pr(\varepsilon > -[\alpha + \beta x]|x) \quad (7)$$

This equation shows that the probability depends on the probability distribution of the error term. Two distributions of the error term are commonly assumed, both having a mean of 0. The first one assumes that the error term is normally distributed with $\text{Var}(\varepsilon) = 1$. This yields a binary probit regression model, where equation (6) above becomes:

$$\Pr(y = 1|x) = \int_{-\infty}^{\alpha + \beta x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \quad (8)$$

Alternatively, when the error term is assumed to be logistically distributed, a logistic regression model can be employed. This study assumed a probit model, because the data were standardised during the principal component analysis, and, so, the error term were assumed to be normally distributed.

For both probit and logit models, the probability of an event occurring is the cumulative density function (*cdf*) of the random disturbance term evaluated given values of the independent variables:

$$\Pr(y = 1|x) = F(x\beta) \quad (9)$$

where F is the cumulative density function of the normal distribution for the probit model.

The chosen model expressed the observed outcome in terms of a latent variable given by:

$$y_i^* = \beta_0 + \beta_j x_{ij} + e_i \quad (10a)$$

$$y = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \quad (10b)$$

Where y_i^* is the latent variable for drought resilience, for household i ; β_j represents parameter j to be estimated; x_{ij} represents explanatory variable j for household i , and $e_i = N(0, \sigma^2)$ is the normally and identically distributed random error term.

The probit regression model that was used to identify the determinants of resilience was:

$$\begin{aligned} \text{Resilience} = & \beta_0 + \beta_1 \text{Gender} + \beta_2 \text{Age} + \beta_3 \text{HHSize} + \beta_4 \text{Educ} + \beta_5 \text{Land} + \\ & \beta_6 \# \text{Chickens} + \beta_7 \# \text{Goats} + \beta_8 \# \text{Bicycles} + \\ & \beta_9 \# \text{family members outside household} + \\ & \beta_{10} \text{Frequency of dry spells over 5 yrs} + \beta_{11} \text{Participation in VSL} \end{aligned} \quad (11)$$

where $\text{Resilience}=1$ if the household has a resilience score of greater than 0 and $\text{Resilience}=0$ otherwise; Gender is the gender of the household head (1=female, 0=otherwise); Age is the age of the household head (years); HHSize is the size of the farm family (number of people); Educ is the number of years spent in primary school; Land is the area of land (acres) owned by the farming household; $\# \text{Chickens}$ is the number of chickens owned by a farming household; $\# \text{Goats}$ is the number of goats owned by a farming household; $\# \text{Bicycles}$ is the number of bicycles owned by the farming household; $\# \text{family members outside household}$ is the number of immediate family members living outside the household; $\text{Frequency of dry spells over 5 years}$ is the number of times a farming household was affected by dry spells over the previous five-year period; and $\text{Participation in VSL}$ is a dummy variable for participation in village savings and loan (VSL) activities.

2.2.3. MODEL FOR THE EFFECT OF DROUGHT RESILIENCE ON FARM HOUSEHOLD WELFARE

In order to test the second hypothesis – that drought resilience does not have any significant effect on the welfare of farming households – a stochastic production function for maize is estimated. The stochastic frontier approach is a parametric technique that uses the standard production methodology. The work on stochastic frontier was pioneered by Farrell (1957), which was followed by the work of Aigner, et al. (1977) and Battese (1992), among other authors. According to Aigner et al. (1977), other methods that were used to estimate the production frontier had some limitations which the stochastic frontier approach addressed.

The estimation of a stochastic frontier begins by assuming that the maximum possible output as a function of inputs given can be denoted by:

$$Y = (x\beta) \quad (12)$$

where Y is the estimated output; x represents a vector of inputs; and β represents a vector of parameters to be estimated.

In the early work of estimating production functions, most researchers used Ordinary Least Squares (OLS) regression techniques to estimate the production functions. This is given as:

$$Y_i = (x\beta) + v_i \quad (13)$$

where v_i represents the error term. This approach assumes that all firms are efficient in their production processes and that all deviations from the efficient output level are due to some noise caused by missing variables or errors in measurement.

Other researchers, including Farrell (1957), used a deterministic approach to estimate production functions. This approach fits a deterministic frontier over the data and assumes that there is no noise in the data and that all deviations are due to inefficiency in production. This approach is presented as:

$$Y_i = (x\beta) - u_i \quad (14)$$

where u_i represents the inefficiency component.

The stochastic frontier approach recognises that the “the production process is subject to two economically distinguishable random disturbances with different characteristics” (Aigner et al. 1977, 24). This approach tries to create a balance by adding the two error terms, one for the noise and another for technical inefficiency to make it possible to undertake standard hypothesis tests. The trans-log functional form of the stochastic frontier is given as:

$$\ln Y_i = \beta_0 + \sum_{n=1}^N \beta_n \ln x_n + 1/2 \sum_{n=1}^N \sum_{m=1}^M \beta_{mn} \ln x_n \ln x_m + v_i - u_i \quad (15)$$

There are two reasons for why the trans-log stochastic frontier approach is preferred over the standard Cobb-Douglas. The first is because of its ability to exhibit non-constant marginal productivity. This implies that the trans-log function can exhibit increasing, decreasing, constant, or negative marginal products simultaneously. The second reason is that more than two variables are used in the model, so the assumption of constant elasticity of substitution required by the Cobb-

Douglas model would be unattainable. In addition the assumptions of homogeneity and separability in the conventional Cobb-Douglas imposes more restrictions on the model, which would bias the estimates.

The trans-log form of the model that was estimated for this study is:

$$Y_i = \beta_0 + \beta_1 Land + \beta_2 Labor + \beta_3 Capita + \beta_4 Seed + \beta_5 DRI + v_i - u_i \quad (16)$$

where; Y_i is the maize output (kg) for household i ; $Land$ is the actual amount of land (acres) used by household i in producing maize; $Labor$ is the amount of labor (person hours) used by household i in producing maize; $Capital$ is the amount of Kwacha (MK) used in other farm activities apart from purchasing inputs for maize production; $Seed$ is the actual amount of maize seed (kg) planted by household i ; DRI represents the Drought Resilience Index for household i ; β_i represents a vector of parameters to be estimated for each household i ; $v_i \sim N(0, \delta_v^2)$ is a two-sided error term representing stochastic noise for each household i , and $u_i \geq 0$ is a one-sided error term representing technical inefficiency for each household i .

All the factors of production are expected to be positively correlated with production, but there is no *a priori* expectation for the sign of the Drought Resilience Index. The DRI was included in the model to measure the effect of drought resilience on household welfare. A positive sign on the parameter for the DRI would mean that households that are resilient are more likely to have improved welfare as compared to those households that are less resilient, *ceteris paribus*.

3. ESTIMATIONS AND RESULTS

In this section we show results from the various analyses that were conducted in the study. Table 3.1 provides summary statistics for the variables that were used in analyses. It is important to note that the 'relatives outside household' variable measured the number of immediate family members that live outside the household and was used in the study as a proxy for remittances. The variable participation in village savings and loans (VSL) was used as a measure of benefits that a household derives from social capital.

Table 3.1: Descriptive statistics for variables used in the analyses

Variable	Units	Mean	Standard Deviation
Age of household head	Years	46.0	16.27
Years of primary education	Years	3.2	3.13
Household size	Number of people	5.6	2.13
Relatives outside household	Number of people	2.7	2.32
Land Holding size	Acres	2.6	1.53
Labor	Person-hours	99.1	63.90
Capital (Investment)	Malawi Kwacha	5,056.0	12,125.24
Seed	Kilograms	9.5	6.24
Output	Kilograms	545.0	453.49
Gender	1 = female; 0 = otherwise	0.3	0.44
Participation in VSL activities	1 = participated; 0 = otherwise	0.3	0.45
Possession of radios	Number of radios	1.1	0.27
Possession of bicycles	Number of bicycles	1.1	0.32
Possession of goats	Number of goats	3.9	3.67
Possession of chickens	Number of chickens	5.2	5.11
Frequency of dry spells	Reported cases over a five year period	2.7	0.87

Source: Author's computations from study survey. 427 observations. VSL – village savings and loan.

Note: Land was measured in acres because the mean landholding size was slightly above one hectare, which could lead to negative values if natural logs were taken during data transformations:

3.1 Estimation of the Drought Resilience Index (DRI)

Table 3.2 is a correlation matrix for the variables used in constructing the DRI. A high correlation of 0.6475 is seen between the production in a good year and production in a bad year variables. Similarly, the months with food after a good cropping season and months with food after a bad cropping season also had a high correlation of 0.505. This is expected because variables that correlated highly measure the same construct. The first two variables measure the amount of food produced in good and bad years, respectively, meaning that the two indicators were production indicators. The last two variables measure the number of months a household consumed home produced food in good and bad years, respectively.

Table 3.2: Correlation matrix for variables used in constructing the drought resilience index

	Production good year	Production bad year	Months with food after a good cropping season
Production bad year	0.648		
Months with food after a good cropping season	0.115	0.121	
Months with food after a bad cropping season	0.102	0.068	0.505

Source: Author's computations from study survey.

Since the correlations provided by the correlation matrix were not assessed as to whether they were suitable or not for use in the principal component analysis (PCA), the Bartlett's test of sphericity was conducted on the data. The objective of the test is to test the hypothesis that the variables used in the PCA were not inter-correlated and that any non-zero correlations in the sample matrix are due to sampling error.

Table 3.3: Results of the Bartlett's test of sphericity

Determinant of the correlation matrix	0.424
Bartlett test of sphericity	
Chi-square	363.9
Degrees of freedom	6
p-value	0.000
H0: Variables are not inter-correlated	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	
KMO	0.516

Source: Author's computations from study survey.

The results in Table 3.3 show that the null hypothesis that the data were not suitable for dimension reduction is rejected. The statistical decision that is made based on these results is that the inter-correlation matrix did not come from a population in which the inter-correlation matrix is an identity matrix. We conclude that the variables used in the study were inter-correlated and that the correlations did not result from a sampling error. This means that the variables are suitably correlated to warrant the application of PCA on the data.

Another important assumption for use of PCA on the data is that the sample size must be large enough. This assumption is measured using the Kaiser-Meyer-Olkin measure of sampling adequacy. The KMO value of 0.516 falls slightly above the threshold value of 0.500, thereby allowing for PCA to be applied on the data. The relatively small value of the KMO, however, implies that the degree of common variance among the variables is not very large. This means that if PCA is applied on the data, the components will account for a fair, but not substantial, amount of variance. Since the data met the minimum requirements for both the Bartlett's test of sphericity and the KMO, the data were considered suitable for dimension reduction using PCA. Table 3.4 shows the PCA results.

Table 3.4: Results of the un-rotated principal components analysis

Component	Eigen value	Difference	Proportion	Cumulative
1	1.792	0.430	0.448	0.448
2	1.362	0.865	0.340	0.788
3	0.497	0.147	0.124	0.912
4	0.350	.	0.087	1.000

N=427; Components = 4; Trace = 4; Rho = 1.0000

Source: Author's computations from study survey.

In the initial solution, each of the variables was standardized to have a mean of zero and a variance of one. For the four variables used, the total variance that must be explained is 4.0. Since a variable can only account for one unit of the variance, a useful variable must account for more than one unit of variance or it must have an eigen value of greater than one. The first principal component explains 44.8 percent of the total variance, while the second explains 34.0 percent of the total variance, which is considered fair enough to use in further analysis. The results also show a trace of 4, which is the sum of entries along the main diagonal of the correlation matrix. The Rho value of 1.000 means that all of the variance is explained by the variables used.

The components were compared to *a priori* expectations to choose the one for use in constructing the index. In order to select which variables to use, it was important to obtain component loadings, which are given as eigen vectors. The

values for the intersection of each variable and component in Table 3.5 represent component loadings. These are correlations between the variables and the components. The first component meets *a priori* expectations on the sign and is then used in constructing the index.

Table 3.5: Eigen vectors from the principal components analysis

Variable	Component 1	Component 2	Component 3	Component 4	Unexplained
Production in good year	0.581	-0.400	0.116	-0.700	0.000
Production in bad year	0.573	-0.416	-0.074	0.702	0.000
Consumption months in good year	0.423	0.561	-0.706	-0.087	0.000
Consumption months in bad year	0.394	0.593	0.695	0.103	0.000

Source: Author's computations from study survey.

Using the results for the first component, which are used as weights, the DRI is generated using the formula:

$$\begin{aligned}
 \text{Drought Resilience index} = & 0.581 * \text{production in good year} + \\
 & 0.573 * \text{production in bad year} + \\
 & 0.423 * \text{months with food after a good cropping season} + \\
 & 0.394 * \text{months with food after a bad cropping season}
 \end{aligned} \tag{17}$$

The formula given in equation (17) is applied to the data to generate the drought resilience index for each survey sample household. Table 3.6 provides summary statistics for the DRIs generated.

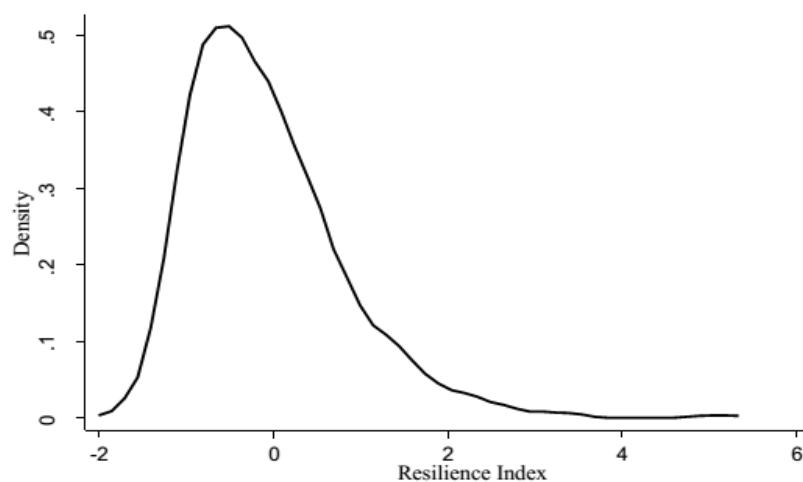
Table 3.6: Summary statistics for the drought resilience index (DRI)

	n	Mean	Std. Dev.	Min	Max
DRI	427	-0.086	0.881	-1.797	5.114
DRI >= 0	163	0.792	0.750	0.007	5.114
DRI < 0	264	-0.627	0.373	-1.797	-0.013

Source: Author's computations from study survey.

According to Table 3.6, an average household in the study area has a mean drought resilience index of -0.086. Since the scores were normalised with a mean value of 0 and a standard deviation of 1, the threshold for identifying a household as resilient or not is set at 0. The observed results suggest that an average household in the study area is not resilient to the adverse effects of dry spells and drought. A high standard deviation compared to the mean score indicates that there is considerable variability in the calculated resilience scores among farming households in the study area. The table also reveals that 163 households, representing 38 percent of households were resilient to effects of dry spells. Figure 3.1 shows the kernel density distribution of the estimated drought resilience indices for the study households.

Figure 3.1: Kernel density estimate of the drought resilience index



Source: Author's computations from study survey.

It can be seen from Figure 3.1 that resilience indices are skewed to the left, meaning that the majority of households in the study area are less resilient and, hence, vulnerable to the adverse effects resulting from the occurrence of drought. Since the study includes areas of two Traditional Authorities, it is important to compare summary statistics for the resilience indices by Traditional Authority, as shown in Table 3.7.

Table 3.7: Drought resilience indices in the Traditional Authorities of Ndindi and Kambalame

Traditional Authority	N	Mean	Standard Error	Standard Deviation
Ndindi	184	-0.278	0.057	0.766
Kambalame	243	0.060	0.060	0.935
Combined	427	-0.086	0.043	0.881
Difference		-0.338	0.085	
difference = mean(Ndindi) – mean(Kambalame)				t = -4.000
Ho: diff = 0				degrees of freedom = 425
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0
Pr(T < t) = 0.0000		Pr(T > t) = 0.0001		Pr(T > t) = 1.0000

Source: Author's computations from study survey.

The results in Table 3.7 suggest that an average farm household in the area of Traditional Authority (TA) Kambalame is relatively more resilient compared to an average household in TA Ndindi. This is evidenced by a t-value of -4.000 and a p-value of 0.0001 for a two sided test. This result confirms sentiments made by the agriculture officer for the area that TA Kambalame has some areas that are less affected by dry spells than most areas in TA Ndindi within the study area. This could be explained by the observation that a large area of TA Kambalame is wetter, being close to Lake Malawi and with a large river flowing through it, while most land in the study area in TA Ndindi receives less precipitation. Table 3.8 compares mean maize production levels in the two areas;

Table 3.8: Mean maize production levels in the Traditional Authorities of Ndindi and Kambalame, kg/acre

Traditional Authority	N	Mean	Standard Error	Standard Deviation
Ndindi	184	434.7	29.07	394.27
Kambalame	243	628.5	30.65	477.72
Combined	427	545.0	21.95	453.49
Difference		-193.8	43.36	
difference = mean(Ndindi) – mean(Kambalame)				t = -4.469
Ho: diff = 0				degrees of freedom = 425
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0
Pr(T < t) = 0.0000		Pr(T > t) = 0.0000		Pr(T > t) = 1.0000

Source: Author's computations from study survey.

Farmers from the study area in TA Ndindi harvest relatively less output than do their counterparts in TA Kambalame. This is evidenced by results from the two-sided t-test where a t-value of -4.469 is obtained with a p-value of 0.0000, hence, rejecting the hypothesis that mean production levels for the two groups are equal. This result provides part of the explanation of the observed differences in the mean resilience scores for farmers in the two study areas.

3.2 Determinants of household resilience to dry spells

Table 3.9 shows the results of the probit regression model to determine the importance of factors that were considered as potentially affecting drought resilience among farming households in the study area. The explanatory variables age and age-squared were found to be collinear. Hence, the age-squared variable was dropped from the model to control for the problem of multi-collinearity. Robust standard errors are used to take care of the possible heteroskedasticity in the data.

Table 3.9: Results of probit regression model and marginal effects of determinants of household drought resilience

Dependent variable: 1 if household has a drought resilience index score > 0; 0 otherwise.

Explanatory variable	Coefficient	P-value	Marginal effect	P-value
Female household head (0/1)	-0.1601 (0.1725)	0.349	-0.0596 (0.0631)	0.341
Age of household head (years)	0.1595** (0.0687)	0.031	0.0602** (0.0258)	0.031
Size of household (persons)	0.3426*** (0.0725)	0.000	0.1293*** (0.0273)	0.000
Years spent in school by household head	0.1072 (0.7490)	0.144	0.0404 (0.0283)	0.144
Land holding size (acres)	0.3923*** (0.0890)	0.000	0.1481*** (0.0339)	0.000
Chickens, number	0.0704 (0.0809)	0.378	0.0266 (0.0306)	0.378
Goats, number	0.0936 (0.0903)	0.264	0.0353 (0.0341)	0.265
Bicycles, number	0.0153 (0.0740)	0.839	0.0056 (0.0279)	0.839
Immediate family members in cities, number	0.0662* (0.0338)	0.060	0.0249* (0.0127)	0.060
Frequency of dry spells over 5 year period	-0.0366 (0.0769)	0.641	-0.0138 (0.0290)	0.642
Participation in village savings and loans	0.2393 (0.1554)	0.119	0.0916 (0.0601)	0.123
Constant	-0.3302 (0.2258)	0.155		

N = 427; Wald Chi² (11) = 79.8; Prob. > Chi² = 0.000; Log pseudo likelihood = -236.25; Pseudo R² = 0.168; y = Pr(Resilience) = 0.370

Source: Author's computations from study survey.

Note: ***1% level of significance, **5% level of significance and *10% level of significance. Values in parentheses are robust standard errors.

The coefficients for all explanatory variables meet *a priori* expectations on their signs. The variables age of household head, size of household, amount of land held (acres), and number of immediate family members living outside the household significantly affect the resilience of farming households to drought. Cameron and Trivedi (2005) argue that the primary value of binary outcome models comes in determining the marginal effect of change in a regressor on the conditional probability of the expected outcome – thus, that $y = 1$. Consequently, the model results in Table 3.9 are also presented as marginal effects.

Age of the household head – Age of the household head affects resilience of a farming household to drought. For every year increase in the age of the household head, the probability of the household becoming resilient to dry spells and drought increases by 0.06, holding all other factors at their mean values. This could be because older household heads have experience in adopting other ways of obtaining their livelihoods much more quickly when a shocks affects a household as compared to their young counterparts.

Another explanation for this result could be that older members have well established social networks in the community, such that it may be relatively easy for them to ask for help from a wider network of friends and relatives in times of need as compared to their younger counterparts. This perspective is consistent with Andersen and Cardona (2013) who found that age of the household head had a positive and significant effect in determining resilience to adverse shocks in Bolivia. The findings, however, do not agree with Keil et al. (2006), who found that age had a positive but insignificant effect on resilience to the adverse effects of dry spells. However, the difference with the findings of Keil et al. (2006) could be due to differences in the analytical methods used and the contexts in which the studies were conducted.

Size of the household – Size of the farm household significantly affects resilience of a household to drought. The results of the marginal effect on the variable size of the household suggest that for a one-person increase in the size of the household, the probability of the household becoming resilient to the adverse effects of drought increases by 0.13, holding all other factors that affect resilience at their means. The result is consistent with Keil et al. (2006) who determined that household size had a positive and a significant effect on household resilience. This result could be explained by relatively larger households likely having enough labor capacity for working their farmland effectively, even under conditions of drought, holding all other factors constant, and would produce more output.

The other argument for this observation could be that large households are more likely to have diversified sources of income, and, hence, be more resilient to economic shocks, such as drought, as compared to smaller households. This, however, does not come without contradiction, because of the challenges that are associated with larger households, such as the need for more food for the household. This results is, thus, confusing in the context of Malawi.

Landholding size – Landholding size was also found to significantly affect the resilience of a farming household to drought. The marginal effect coefficient implies that increasing the amount of land used by a farming household by one acre increases the probability that a household becomes resilient by about 0.15, holding all other factors at their mean levels. This result likely is explained by the fact that households that have more land and use it for producing food may harvest more food compared to a household that has less land.

This result is consistent with Scott et al. (2014) who determined that an increase in own cultivated farmland was associated higher welfare levels in Ethiopia. Households that own large pieces of land generally have incentives to invest in their land by adopting productivity enhancing technologies, as compared to households that have less land. For example, households that have less land are less likely to fallow their land, because they need to use the full extent every growing season. The implication is that the land gets overused, soil fertility declines, and it becomes less productive. It is also difficult to invest on borrowed land because of the uncertainty that the owner may want the land back when investments in the land have already been made. An example of such investments could be those in irrigation equipment, which are expensive but difficult to transfer off of the land on which they are installed.

Number of immediate family members living outside the household – Results of the analysis provide evidence suggesting that remittances (as represented by the number immediate family members living outside the household) have a positive and significant effect on resilience. The marginal effect implies that increasing the number of immediate family members living outside the household by one person results in a corresponding increase in the probability of a household becoming resilient by 0.02. This result suggests that households that have more relatives living outside the household are more likely to benefit from remittances and hence become resilient. This finding is consistent with Anderson and Cardona (2013), who determined that households that received remittances (both local and international) in Bolivia were 13 times more likely to belong to the resilient group than those that did not. These findings are logical, because remittances provide an opportunity for households that face shocks to cushion their adverse effects, which may have important implications on household purchases and consumption of food in such times.

3.3 The effect of resilience to drought on farm household welfare

The stochastic frontier model was estimated to determine the effect of drought resilience, as proxied by the drought resilience index, on farm household welfare. Table 3.10 shows the results of this stochastic frontier analysis. The results suggest that all signs on the coefficients for all explanatory variables conform to their *a priori* expectations. The household's drought resilience index, together with land, seed, and capital investment are significant in explaining farm household welfare, as measured by farm level output.

Table 3.10: Effect of resilience on farm households' welfare, proxied by farm-level output

Variable	Coefficient	Z	P-value
Drought Resilience Index	0.4475*** (0.0353)	12.69	0.000
Land (log)	0.0752** (0.0358)	2.10	0.036
Seed (log)	0.1786*** (0.0393)	4.55	0.000
Labor (log)	0.0749 (0.0533)	1.41	0.160
Investment (log)	0.045** (0.0077)	5.86	0.000
Constant	5.7835*** (0.2432)	23.78	0.000

Likelihood-ratio test of $\sigma_u=0$: $\chi^2(01)=92.61$;
 Prob. $\geq\chi^2=0.000$

Source: Author's computations from study survey.

Note: ***1% level of significance, **5% level of significance and *10% level of significance. Values in parentheses are robust standard errors.

Drought Resilience Index – The stochastic production frontier was used to determine the effect of drought resilience on farm household welfare. Increased drought resilience has a positive and significant effect on farm household welfare. The results suggest that an increase in drought resilience by one percent results in an increase in farm household welfare by 0.45 percent, holding all other factors constant at their mean values. This indicates that farm households that have a

positive drought resilience index are more likely to have improved welfare as compared to their counterparts who have lower drought resilience.

Land – Findings from the study reveal that land allocated to maize production significantly affects the welfare level of a farming household. A one percent increase in the land area allocated to maize production results in an increase in the welfare of a farming household by 0.08 percent. This means that farmers that use more land are likely to have better welfare than those that use less land, holding all other factors constant at their mean values. This result is consistent to the work of Solis et al. (2007), who found that land area cropped significantly affected the efficiency of producers in El Salvador and Honduras.

Seed – The amount of seed used in maize production significantly affects the welfare of a farming household. The results suggest that for every one percent increase in the amount of seed used in maize production, there would be an increase in household welfare by 0.18 percent, holding all other factors constant at their mean values. Farmers that use more seed are more likely to have improved welfare as compared to those that use less seed. This, however, assumes that the crop is well managed and all other inputs were applied, including adequate rainfall.

Capital Investment – The amount of money (capital) invested in maize production significantly affects farm household welfare. A one percent increase in funds invested in maize production results in an increase in farm household welfare by 0.5 percent, holding all other factors constant. This could be because farmers that invested more capital in maize production purchased inputs, such as fertilizers, which helped increase the level of output. Farmers that invest more money in maize production are more likely to have better livelihoods compared to those who do not invest or who invest less. This may be linked to the fact that farmers that adopt new technologies tend to invest more money on their farms and, hence, earn more output in return. The finding also is consistent with the work of Magreta (2011) who found a positive and significant effect between the technical efficiency of rice producers and their level of investment in fertilizers.

4. CONCLUSIONS AND POLICY IMPLICATIONS

Based on the findings of this analysis of the impact of resilience to drought on farm household welfare in Salima district, three major conclusions are derived. First, only 38 percent of farming households in the area of Chipoka were resilient to drought. Second, several farm household characteristics, including the age of the household head, the size of the household, landholding size, and the number of immediate family members living outside the household, are significant determinants of household resilience to drought. Third, the drought resilience variable was found to be positively correlated with farm level output, implying that households that were resilient were more likely to produce more maize.

Three policy implications follow from this research. First, introducing productivity-enhancing technologies in the area would help to improve the welfare of farmers. For example, increasing access to irrigation technologies will help farmers to better cope with dry spells. This would also help to smooth income among farmers who usually obtain their income after the main harvest season. Second, it would be beneficial to encourage farmers to participate in off-farm livelihood activities, so that they diversify their incomes beyond farming alone. It would also pay off if farmers diversified from maize production. Strengthening fish value chains, for example, would provide a livelihood option for some vulnerable households. Third, for NGOs working in the area, it would be much more beneficial if relief items that come in the area are targeted to needy households based on household characteristics that were determined to affect resilience.

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Acknowledgments

This Working Paper is an output of the Bunda Grant Scheme of the Strengthening Evidence-Based Agricultural Policy (SEBAP) project of IFPRI-Lilongwe. The Grant Scheme provides selected MSc students from the Lilongwe University of Agriculture and Natural Resources (Bunda College) with opportunities to improve, publish, and disseminate the research that they undertook during their MSc training. The SEBAP project is made possible by the generous support of the American people through the United States Agency for International Development (USAID).

However, the views expressed in this working paper imply no endorsement by IFPRI-Lilongwe, USAID, or any other party.

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This Working Paper has been prepared as an output for the Malawi Strategy Support Program (MaSSP) of the International Food Policy Research Institute (IFPRI). It is intended to promote discussion and has not been formally peer reviewed.

MaSSP works closely with the government of Malawi and other development partners to provide information relevant for the design and implementation of Malawi's agricultural and rural development strategies. This MaSSP publication is made possible by the generous support of the American people through the United States Agency for International Development (USAID). The contents of this publication are the responsibility of the authors and do not necessarily reflect the views of USAID, the United States Government, or IFPRI.

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