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## **SMALLHOLDER FARMERS' RESOURCE ALLOCATION DECISIONS IN A MAIZE-FARMING SYSTEM UNDER CLIMATE RISKS IN MALAWI**

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### **ABSTRACT**

Using household data from Lilongwe districts, along with crop phenology, agronomic management and climatic data from Chitedze Research Station, the Target-MOTAD and DSSAT-CSM models examined the resource allocation decisions of smallholder farmers in maize farming systems under climate risk in Malawi. Specific aims were to evaluate the ability of DSSAT to predict and collate DTM and non-DTM yields under climatic risk and to use a bio-economic procedure developed using DSSAT and Target-MOTAD to explore the impact of climatic risk on allocation of resources to DTM and non-DTM production. The paper argues that higher average yields observed from DTM varieties make it the most optimal maize production plan, in maximizing household incomes, food security, and minimizing deviations from the mean while meeting the set target incomes of farmers compared to non-DTM varieties. The multidisciplinary nature of this paper has contributed to the body of research by providing a powerful analytical procedure of modelling farmers' resource allocation decisions in maize based farming systems in Malawi. This study necessitates the use of a combination of biophysical and economic procedures when evaluating promising lines prior to variety release in order to identify the high yielding variety that will continuously bring sustained profits to the farmers amidst climate change.

**Key words:** *Climate risks, Target MOTAD, DSSAT, smallholder farmers, resource allocation.*

### **INTRODUCTION**

Risks and uncertainties, their effects and how farmers react to those risks are major perils to smallholder agricultural production in Malawi where farmers lack information and capacity to predict future weather outcomes (Getnet *et al.*, 2015). In this paper, risk is viewed as uncertainty embedded in the probable outcomes in maize production. Maize farmers are exposed to several risks, namely, price,

market, climate, biological and financial risks (Akhtar *et al.*, 2019). Despite variability in temperature and rainfall, climate risk arises from extreme weather events like drought (or dry spell). In this paper, drought is defined as a natural feature, usually allied with warm and dry weather over an extended period of time (dry spells) causing less than normal water available on the land surface (Masih *et al.*, 2014) required for maize growth. As an agro-based economy, scarcity of climate related data in Malawi makes agricultural productivity to be very unstable for rural smallholder farms.

Analysis of climate risk is very important in agriculture because climatic risks influence smallholder farmers' decisions to allocate resources to agricultural production (Masih *et al.*, 2014). However, in Malawi, limited research has been conducted that links climate related risks to agricultural resource allocation decisions in smallholder maize farming systems. Understanding the decision-making process of smallholder farmers under climate risk is critical for the development of novel strategies like climate-smart agriculture (CSA) for improving farm outputs. CSA is embedded in sustainable agriculture and rural development which, if reached, would contribute towards achieving the Sustainable Development Goals (SDGs) of lowering hunger, and improving management of the environment. Drought tolerant maize (DTM) is one example of technologies promoted under CSA (Lipper *et al.*, 2014). Sub-Saharan African (SSA) countries like Malawi, have progressed considerably in the use of improved maize varieties like DTM (Lipper *et al.*, 2014). DTM is a focal point of this study since it is promoted under CSA in Malawi due to the importance of maize as a major food crop in many Malawian households.

Experimental research has studied the impacts of climatic risks on an array of major crops. The experimental models are used because they provide a systematic means to map variations in climatic and other environmental inputs (Ngwira *et al.*, 2014). Yet, they are nearly not capable of capturing the linkage between climate related risks and farmer resource allocation as they implement adaptation practices (Karali *et al.*, 2013). This study enhances understanding of intricate relationship between economic and ecological aspects at farm level through coalescing information from both biophysical models (like DSSAT) and mathematical programming (MP). The objectives of the paper are (1) to evaluate the ability of DSSAT to predict and collate DTM and non-DTM yields under climatic risk and (2) to use a bio-economic procedure developed using DSSAT and Target-MOTAD to explore how climatic risk influence allocation of resources to DTM and non-DTM production in the sampled region

## **MATERIALS AND METHODS**

### **Study Site**

The study used a farm from Chitedze Research Station in Lilongwe due to the availability of observed DTM and non-DTM maize data and daily rainfall and temperature data required for the analysis.

**Decision Support System for Agro-Technology Transfer (DSSAT) Cropping Systems Model (CSM)**

The CSM-CERES-Maize module (Jones and Kiniry, 1986) was used and is based on the effects of weather, soil characteristics and crop management practices. The drought tolerant SC 403 and non-drought tolerant MH 18 from the sampled experimental field were used. To evaluate the biophysical model, the CERES-Maize model requires six genetic coefficients that govern the life cycle and reproductive growth of maize varieties as provided in Table 1 for the varieties.

Table 1. Calibrated genetic plant growth coefficients of maize varieties used in CERES-Maize model for SC403 (DTM) and MH 18 (Non-DTM)

Coefficient	Description	SC 403	MH 18
P1	Thermal time (degree days above the base temperature of 8°C) from seedling emergence to the end of juvenile stage.	235.0	245.0
P2	Photoperiod sensitivity associated with delayed growth under unfavourable long day length condition (no unit)	0.27	0.28
P5	Thermal time from silking to physiological maturity (degree days above the base temperature of 8°C in the maturity stage)	800.0	843.0
G2	Potential maximum number of kernels per plant	630.0	417.3
G3	Kernel filling rate under optimum condition (mgd-1)	7.0	7.87
PHINT	Interval in thermal time between successive leaf appearance (degree days above a base temperature of 8°C)	38.90	75.0

\*Source: Ngwira *et al.*, 2014; Tesfaye *et al.*, 2015

**Statistical Analysis**

The Root Mean Square Error (RMSE) and mean percent difference (MPD – obtained as the mean of %D) were used to evaluate the performance of DSSAT (Ngwira 2014).

$$RMSE = \left[ \left( n^{-1} \sum (Yield_{simulated} - Yield_{observed}) \right)^2 \right]^{0.5}$$

$$\%D = \left[ \frac{Yield_{observed} - Yield_{simulated}}{Yield_{observed}} \right] \times 100$$

The RMSE value of zero indicated the goodness of fit between simulated and observed data. High values of *D* that are close to 1 indicate good model performance and better relation of observed versus simulated yields.

### Target MOTAD Model to Determine the Optimal Production of Maize

The Target MOTAD was used to determine optimal resource allocation in the production of maize. Type of maize has been specified according to drought or non-drought tolerance. The main activities in the Target-MOTAD model include maize production related with three states of nature, seasonal labour used, maize crop sales and capital used in maize production. The model defines several constraints that are faced by a maize farmer such as limited amount of land and labour use, limited cash for input purchase using the available resources at farm household and the states of nature related to climate risk. The model was run in the General Algebraic Modelling System (GAMS) software (Version 25.0.2). Table 2 presents the three states of nature related to climate risk from Chitedze research station. The results indicate that both rainfall distribution and rainfall amount are average in the study area for about 75% of the times. Furthermore, about 12.5% of the times, rainfall distribution was bad while rainfall amount was average and for the other 12.5% of the times rainfall distribution was average whilst amount of rain was poor. The data used to compute the probabilities in Table 2. relates to daily rainfall data collected between 2006 and 2016 at Chitedze Research Station.

Table 2. States of nature linked to weather risk at Chitedze Research Station

	Rainfall amount		
Rainfall distribution	Poor (413.6<R*<620.5)	Average (620.5<R*<1034.1)	Good (R>1034.1)
Bad (SD*>121.7)	Not applicable	0.1	Not applicable
Average (73<SD*<121.7)	0.1	0.8	Not applicable
Good (SD*<73)	Not applicable	Not applicable	Not applicable

Key: SD\* = standard deviation for rainfall amount; R\* = Rainfall amount (mm).

\*Source: Chitedze Research Station Meteorological Service Department (2017)

### The Objective Function

The Target MOTAD model followed Tauer (1983) and was set as follows.

$$Max (Z) = \sum_{d=1}^3 \sum_{j=1}^2 [E(\bar{C}_{dj})(x_{dj})]$$

Where;  $E(\bar{C}_{dj})(x_{dj})$  is the expected gross margin in MK for maize category  $j$  in rainfall state of nature  $d$  grown under the rain-fed condition,  $\bar{C}_{dj}$  is the gross margin per ha,  $x_{dj}$  is the crop acreage,  $d$  is the 3 rainfall states of nature namely; good, average and poor as classified from the rainfall monthly data from 2006 to 2016 and  $j = 1,2$  is DTM and non-DTM maize categories whose yields were simulated from the DSSAT crop model

**Constraints**

**Labour Constraint**

The amount of labour required per hectare to produce maize crop type  $j$  in rainfall state of nature  $d$  under rain-fed conditions is specified as

$$\sum_{d=1}^3 \sum_{j=1}^2 l_{dj} x_{dj} \leq W_d \quad (j = 1,2)$$

Where;  $W_d$  is the amount of labour in man-days that is available in rainfall state of nature  $d$ ,  $l_{dj}$  is the amount of labour in labour hours required to produce one hectare of DTM and non-DTM maize crop type ( $j$ ) under rain-fed conditions,  $x_{dj}$  is the amount of land allocated to activity  $j$  measured in hectares

**Land constraint**

The specification of the land constraint is as follows:

$$\sum_{d=1}^3 \sum_{j=1}^2 h_{dj} x_{dj} \leq L_d \quad (j = 1,2)$$

$L_d$  is all the land available for cropping while  $h_{dj}$  is all the land area required to produce per hectare of maize crop type  $j$  in rainfall state of nature  $d$

**Capital constraint**

$$\sum_{d=1}^3 \sum_{j=1}^2 r_{dj} x_{dj} \leq R_d \quad (j = 1,2)$$

This constraint represents ( $r_{dj}$ ) the amount of cash capital measured in Malawi Kwacha deflated by year 2012 which is the base year required to produce per hectare of maize crop type  $j$  and  $R_d$  is the amount of cash capital available at the start of the cropping season in rainfall state of nature  $d$ .

**Maize self-sufficiency constraint**

Estimation of the maize self-sufficiency constraint was based on the annual maize requirement of each member of the household according to their ages.

$$\sum_{d=1}^3 \sum_{j=1}^2 f_{idj} x_{dj} \geq F_d \quad (i = 1,2)$$

Where;  $f_{dj}$  is the yield of maize produced per hectare of maize crop type  $j$  in kg/ha while  $F_d$  is the annual amount of maize required for the household in kg in rainfall state of nature  $d$

**Negative deviation from a pre-specified target revenue constraint**

This constraint is presented as:

$$\sum_{d=1}^3 \sum_{j=1}^2 c_{dj} x_{dj} + Y_k \geq T \quad \text{for all } k$$

Where;  $Y_k$  are the deviations below target income during rainy season for the  $k^{\text{th}}$  state of nature.  $T$  represents target income during the rainy season. The states of

nature are defined as a particular set of probabilities representing years of good, average, and poor rains during the year of crop simulations.

### **Sum of negative deviations multiplied by the probabilities of the states of nature constraint**

Tauer (1983) considered that during the planning period of a decision maker, perception of risks entails that the total deviations have to be confined to a specific value. Hence, to define this aspect of risk perception, he equated the sum of the product of probabilities of each states of nature and the deviation associated with the appropriate state of nature as specified below;

$$\sum_{k=1}^3 p_k y_k \leq \lambda$$

Where; K is the number of states of nature,  $p_k$  is the probability of the  $k^{\text{th}}$  state of nature; and  $\lambda$ , a risk parameter represents the sum of expected negative deviations below the target income in MK.

## **RESULTS AND DISCUSSION**

### **Evaluation of Simulated DTM and non-DTM**

The evaluated CERES-Maize model verified a good agreement between observed and simulated grain yield data (Table 3). The model methodically simulated maize grain yield for all treatments with differences ranging from -5.3 to 9.6%, 2.8 - 10%, -2.1 to -16.7%, 4.6 - 5.2% and 4.6 - 5.2% for 2006 –2007, 2007–2008, 2008–2009, 2011–2012 and 2014 – 2015 growing seasons respectively. Overall, the RMSE were found to be 758.3 kg ha<sup>-1</sup> 394.2 kg ha<sup>-1</sup> 458.9 kg ha<sup>-1</sup> 402.2 kg ha<sup>-1</sup> and 570.0 kg ha<sup>-1</sup> for 2006–2007, 2007–2008, 2008–2009, 2011–2012 and 2014–2015 growing seasons, respectively as shown in (Table 6.1). Similarly, MPD were found to be as 4.7 %, 6.4%, 2.4%, 8.5% and 0.1% for 2006–2007, 2007–2008, 2008–2009, 2011–2012 and 2014–2015 growing seasons, respectively. This comparison shows that the model has the potential to simulate maize yield for an independent data set of the given years. Therefore, performance of CERES-Maize model was acceptable under a given set of conditions. As such, the model was used for further decision-making on maize variety choices.

### **Prediction of Maize Grain Yield**

Predicting maize grain yield necessitates developing and fine-tuning the promoted maize varieties in Malawi (Ngwira *et al.* 2014). Results in Table (4) divulge significant differences ( $P < 0.01 - p < 0.05$ ) between DTM and non-DTM yields from years 2006 to 2007 and 2011 to 2015. Mean maize yields for DTM were more than non-DTM from 2006 to 2014. The differences were much higher ( $>20\% \text{ ha}^{-1}$ ) in years 2006, 2007 and 2014 by 22.19% ha<sup>-1</sup>, 27.80% ha<sup>-1</sup> and 24.34% ha<sup>-1</sup> respectively. These findings concur with the findings of Tesfaye *et al.* (2018) who reported more yields for DTM compared to other maize varieties that lacks heat tolerance genes.

Table 4. Simulated maize grain yield (kg) for DTM and Non-DTM, Chitedze Research Station

Maize Type	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
DTM	5382	5904	4309	4339	4264.6	4790	5021	5238	5052	4134
Non-DTM	4188	4263	4280	4217	4034.0	4023	4582	4230	3822	4333
P-value	0.000	0.000	0.919	0.704	0.490	0.002	0.041	0.004	0.000	0.000

### Target-MOTAD Analysis Simulated DTM and non-DTM under Alternative Rainfall Scenarios

#### Risky Neutral Situation

Under the risk neutral case, the higher marginal value of MK551,500.00 imply that the resource has a bigger marginal effect on the objective function. Likewise, the slack of MK40, 000 and 68.28 labour hours is clear evidence that not all capital and labour were used respectively. The maize sufficiency requirement had no effect on the objective function due to its zero marginal value.

Table 5. Optimal resource levels from the risk neutral case

Resource	Value	Used	Unused	Marginal value (MK)
Land (ha)	2.1	2.10	0.0	551,500.00
Capital (MK)	250,000.00	210,000.00	40,000	0.0
Labour (man hours)	1400	1331.72	68.28	0.0
				<b>Marginal</b>
<b>Maize sufficiency requirement (kg)</b>	<b>Maize produced</b>	<b>Marginal value (MK)</b>		
Bad-average	3,000	0.0		
Poor-average	3,000	0.0		
Average-average	3,000	0.0		

#### Risky Situation

Risk was introduced in the optimization problem as the negative deviation from mean income following Watts *et al.*, (1984) by varying target income to assess the negative deviations from the mean (risk levels) to achieve the third objective and to test the third hypothesis. The target income used for this analysis has been calculated as the annual income needed to cover fixed costs. These include those variable costs not already accounted for in the calculation of net returns i.e. the cost of basic food commodities e.g. salt, sugar, relish etc. A set of 10 efficient farm plans (Table 6) was obtained by parameterising the level of risk (deviations from

mean income) from MK 48,706.20 average deviation to MK5,411.77 (Table 6). These farm plans maximise expected income for a given risk level, subject to minimised negative deviations from the target income. The variations in risk and optimal solutions are obtained until all feasible possible changes occur, and the value of expected income cannot be improved by increasing the level of risk. The Target MOTAD solutions (Table 6) indicate that at higher target income levels, the risk is also high. Furthermore, land was constantly allocated to DTM at all risk levels and they attracted the same mean income despite the state on nature. The results imply that with the target income met, farmers have optimally achieved the 3000kg annual food requirement, thus achieving their household food security. These results lead to a conclusion that farmers must allocate all their resources (land, capital, and labour) to DTM when risk increases regardless of the state of nature. These findings concur with the findings of Tesfaye *et al.* (2018) who reported more yields for DTM compared to other maize varieties that lacks heat tolerance genes.

Table 6. Trade-offs between risk (negative deviations from target income) and mean income, with associated enterprise combinations-Target-MOTAD Model

Farm Plan	Mean Income (MK)	Target income (MK)	Negative Deviations ( ) from mean Income	Enterprise Mix (ha)	
				DTM	Non-DTM
1	1,158,142.01	1,028,242.00	48,706.20	2.10	0.00
2	1,158,142.01	974,124.00	43,294.40	2.10	0.00
3	1,158,142.01	920,006.00	37,882.60	2.10	0.00
4	1,158,142.01	865,888.00	32,470.80	2.10	0.00
5	1,158,142.01	811,770.00	27,059.00	2.10	0.00
6	1,158,142.01	757,652.00	21,647.20	2.10	0.00
7	1,158,142.01	703,534.00	16,235.40	2.10	0.00
8	1,158,142.01	649,416.00	10,823.60	2.10	0.00
9	1,158,142.01	595,298.00	5,411.77	2.10	0.00
10	1,158,142.01	541,180.00	0.03	2.10	0.00

Note: is the maximum allowable income deviation from the target (the risk aversion coefficient)

Figure 1 below shows the Target-MOTAD risk income frontier at all levels of target income. According to the figure, higher levels of expected incomes are associated with higher negative deviations (risks). This means, along the graph, a maize farmer will maximize profits despite higher levels of risks. This implies that regardless of which state of nature, farmers who grow DTM are expected to get higher profits which will be even higher at higher risk levels.



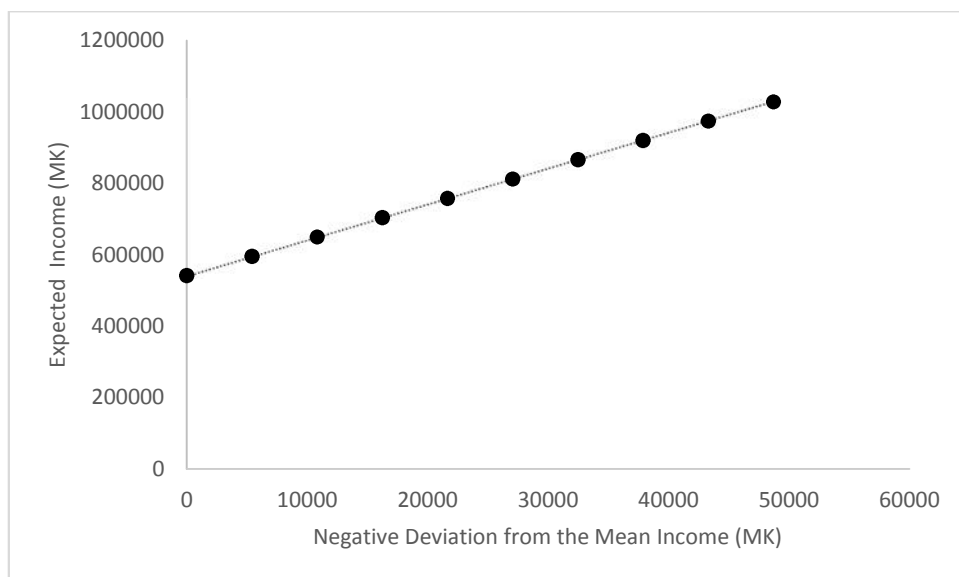


Figure 1. Efficient set of expected income and negative deviation from mean income on a maize farm

### CONCLUSION

The validation of DSSAT model was successful since it was able to simulate the maize yields adequately thus mimicking what is happening on the ground. The study has further shown that adoption of DTM in climate risk prone areas might prepare smallholder farmers for the coming future threats of climate variability during bad years to improve food security situations in their areas. From the simulated maize yields for DTM and non-DTM, the performance of maize was largely affected by climate since the agronomic practices were followed as required. Finally, the use a bio-economic procedure developed using DSSAT and Target-MOTAD has exhibited a methodological contribution to the growing body of academic literature on climate variability and agricultural economics. For instance, while few economic models explicitly consider risk in the objective functions, they slackly assume normal distribution of climatic variables such as rainfall and temperature. Using the case of Chitedze research, the Target-MOTAD model incorporates farmers risk attitude and rainfall distribution to assess farmer's resource allocation decisions in response to climate variability by considering three important issues; the farmers risk attitude, the use of simulated maize yields from DSSAT plus incorporation of three states on nature that captured rainfall distribution and amounts.

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