Multi-Site Bundling of Drought Tolerant Maize Varieties and Index Insurance

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Abstract

We investigate the potential for bundling drought tolerant maize varieties (DTMV) with a multi-site rainfall index insurance (RII) within mega-environments. We use unique on-farm trial data conducted by the International Maize and Wheat Improvement Center (CIMMYT) over 49 locations in Eastern and Southern Africa spanning 8 countries and 5 mega-environments in which 19 different DTMV were tested at each location. Spatially correlated daily rainfall are generated from a first-order two-state markov chain process and used to calibrate the index and predict yields with a hierarchical Bayes spatial model. We find that complementing RII with specific drought tolerant maize variety produces contracts with lower premiums and higher guaranteed returns especially in dry lowland mega-environments, thus increasing the chances of scaling up RII within this environment.

Key words: Multi-site index insurance, Drought tolerant maize varieties, Mega-environment, Multivariate hierarchical Bayes, Africa.

JEL classification: O33, Q12, D80, C11.

1 Introduction

Rural households in most developing countries experience severe income and food consumption fluctuations due to drought. This vulnerability has the potential to further escalate given projections of more severe and frequent adverse weather conditions due to climate change, and threatens to rollback achievements in global poverty levels FAO (2007). The effect of drought is compounded by costly decisions made by farmers who often trade off considerable future gains (from adopting new technology) for reduced drought related losses (Eswaran and Kotwal, 1990; Rosenzweig and Wolpin, 1993; Jacoby and Skoufias, 1997).

Over the last decades significant resources have been allocated by donors and governments in developing countries to develop drought tolerant maize varieties (DTMV) and weather index insurance (WII) for farmers to manage drought risk. However, the demand for WII has been very low with little potential for scalability and sustainability (Barnett et al., 2008; Binswanger-Mikhize, 2012). The low demand has been attributed to credit and cash constraints on farmers, competition from informal risk-sharing networks (Hess and Syroka, 2006; Barnett et al., 2008; Molini et al., 2008; Binswanger-Mikhize, 2012), and the complex nature of the technology and the uninsured basis risk it creates (Molini et al., 2008; Hess and Syroka, 2006; Clarke, 2011a) from poor correlation between yield losses predicted by the index and that experienced on individual farms.

On the other hand, significantly higher adoption of improved (and drought tolerant) maize varieties by farmers are being reported (CIMMYT-IITA, 2013; Diiro, 2013) whose development requires high upfront cost but a near zero marginal cost of producing DTMV seeds. These seeds provide farmers with informal insurance protection against mild to moderate drought. However, as drought severity increases beyond a certain point, the yield advantage of DTMV over non DTMV begins to erode, and at severe drought conditions the yield advantage is zero. Contrary, WII requires a meager upfront development cost and has the potential to fully insure households against drought. However, the actuarially fair premiums are costly to farmers and could be perceived as unfair for cash constrained individuals.[1] Designing WII to cover (more severe) drought risk beyond the point where DTMV is losing its yield advantage is expected to significantly lower premiums and offer better benefits to farm households as drought severity increases, thus making contracts more attractive. This will spur demand for WII, reduce underinsurance, and improve the pool and mix of the insured making scalability and sustainability feasible.

However, while there is a seemingly complementary relationship between DTMV and rainfall index insurance WII, very little is known about the exact relationship between the two technologies, including how it varies across space and different drought severity levels, and their potential benefits and limitations. To the best of our knowledge, only one study, Lybbert and Carter (2014), has made this connection using a systematic approach. The authors conceptually demonstrated the complementarity between the two technologies using maize yield data from Ecuador, a hypothetical drought tolerant maize variety, and a hypothetical rainfall index. Even though they found evidence that supports the complementarity between the two technologies and improved benefits, their findings are limited by the assumptions made in their analysis. Other studies have taken a different approach in their investigation. Exploiting interaction between members of a group and the covariate risk they face, Traerup (2011), Dercon et al. (2014) and de Janvry et al. (2014) conceptually argued that the demand for WII can be improved by selling insurance to informal risk-sharing groups instead of individual farmers. Skees and Barnett (2006) and Skees et al. (2007) investigated bundling WII with micro loans to facilitate farmer's access to credit with positive results. However, access to credit does not necessarily ensure acquisition of a drought tolerant variety that highly complements the risk layer insured by a specific WII, and except Lybbert and Carter (2014), no other study has considered the potential benefits and limitations offered by complementing DTMV and WII jointly in a systematic approach.

In this study, we investigate the potential for bundling DTMV with a multi-site and

[1] We note that the insurance ratemaking process used in most pilot programs allows for the premium estimates to be generated from a constrained optimization and the final premium paid is reached through further negotiation between the insurer and the farmers (Osgood et al., 2007).

multi-mega-environment rainfall index insurance (RII) to better insure households against drought risk and facilitate scaling up and sustainability of farm risk management programs. Specifically, we use a unique on-farm trial data conducted by the International Maize and Wheat Improvement Center (CIMMYT) over 49 locations in Eastern and Southern Africa spanning 8 countries (Ethiopia, Kenya, Malawi, Mozambique, Tanzania, Uganda, Zambia and Zimbabwe) and 5 mega environments (dry lowland, dry mid altitude, wet lower mid altitude, low wetland, and wet upper mid altitude) with daily rainfall data over the growing season to empirically conduct our investigations. Extending the framework proposed by Lybbert and Carter (2014), we investigate the potential relationship and benefits from complementing each drought tolerant maize with RII contracts which insure against mild, moderate and severe drought risk in a community and mega-environment. Thus, bundling in this study entails choosing the optimal insurance trigger level (that is, the index point beyond which the contract begins to payout) that complements the drought tolerant trait of a specific maize variety based on density function of drought in the environment.

Results from our analysis show strong potential in bundling DTMV with RII. We find a defined relationship between the index and yield differentials that is invariant to drought severity thus facilitating the calibration and selection of an optimal bundle. Interestingly, we find very high variation in the performance and benefit (premium and certainty equivalent) of a bundle which depend on the maize variety tolerance to drought, the insurance trigger level, and the size and type of environment, with very high chances of selecting an extremely sub-optimal and unattractive contract. Overall benefit and performance estimates show that exploiting the complementarity between DTMV and uninsured covariate risk layers produces a contract with significantly lower premiums and higher certainty equivalent (CE) revenue. More interestingly, the bundle was found to be more beneficial in dry lowland mega-environment than smaller geographic regions, thus showing high potentials for scaling up and sustaining RII programs within these environments. The policy implications of these results are significant given that demand can be increased by systematically bundling the two technologies to produce contracts with lower premiums, and by proceeding with a design that aims to insure all farmers within a dry lowland thereby increasing the area of coverage. Increasing the pool and the mix of insured farmers is necessary for scalability and solvency of the insurance program.

The remainder of the paper is structured as follows. In the next section we discuss the motivation behind the model framework chosen for this study. In section three, we develop the multivariate spatial hierarchical Bayes model use in predicting yields over different drought severity conditions. This section also summarizes the rainfall simulator. We discuss and summarize data use in section four. Next, we present and discuss the results in section five. Finally, we conclude with major findings, policy implications and potential for future research.

2 Motivation for model framework

Maize is a major food crop in most countries in Eastern, Southern and West Africa and accounts for about 53% of all cereals (FAO, 2012) and 70% of total caloric intake (Langyintuo et al., 2010). Maize production in these region is mostly rainfed and highly vulnerable to adverse weather conditions. Yield losses associated with drought range between 10% to 50% on average. Losses are remarkably higher in environments with low soil fertility and other biotic stresses (FAO, 2012). Under likely climate change scenarios, more frequent adverse weather conditions have been predicted making these regions increasingly vulnerable to food insecurity and poverty.

From an agronomic standpoint, DTMV have the ability to significantly reduce yield losses under specific water stress levels, and their potential vary from one agro-ecological region to another. Breeding drought tolerant maize traits adapted to specific regions requires extensive on farm trials posing both financial and systemic constraints. The later being that the specific stress (drought) of interest in the trial may not be observed at the location during the season in which the trial was conducted. When this occurs, genotype performance and stability across environments can not be properly evaluated using data from such trials. While incorporating conventional maize breeding with managed stress screening has been shown viable, on farm trials remain essential in evaluating the performance and stability of genotypes in actual environments. In addition, data from such trials in which several DTMV are consistently tested over space and time is rarely available posing estimation problems.

The on-farm trial data use in this study was conducted in 2011 and involves 20 different DTMV including hybrids, and open pollinated maize varieties. During the trial, less than 14 locations actually experience water stress levels, thus creating data limitations. In addition, there is general absence of long time series for weather data in most developing countries including the regions in this study which adds to the data constraints. Commercial property and casualty insurers require at least 30 years of time series data to properly quantify the probability of dry spell and loss.

We address the data limitation in the first part of our study by developing a model that allows us to effectively predict yields across space and time. Specifically, we use a hierarchical Bayes multivariate spatial model that also allows for spatial correlation and cross correlation among trial sites and agro-mega environments. We simulate correlated space-time growing seasonal rainfall over the 49 locations using a multi-site rainfall simulator (Wilks, 1998), and use it in the posterior predictive distribution to generate yields for the 19 DTMV under different severity levels of water stress. In the next step, following Lybbert and Carter (2014), we calibrate RII with three different trigger points (reflecting mild to moderately severe drought levels at which DTMV is a potential complement) by trial location and agro-mega environment.

To investigate the potential complementarity of DTMV with RII, we examine stability of yields, yield differentials, premiums, certainty equivalent and changes in certainty equivalent revenue afforded by each maize variety across trial locations, agro-mega environments and different levels of drought severity corresponding to rainfall trigger levels for the index insurance. In the final part of our analysis, we estimate and compare the correlation between the indices and the yield and yield differential by location and agro-mega environment.

In practice, bundling DTMV and RII requires the index to be strongly correlated with yield loss, and proper knowledge of the net yield profile for the drought tolerant variety compared to a competing alternative variety. Maize varieties have different tolerance to drought and potentially high variation in yield loss from one variety to another. Moreover, these losses likely vary from one agro-climatic environment to another making it difficult to find a good index over a large area. This serves as a limitation to scale up and sustain index insurance programs. However, a key positive feature is that, a multi-site index can take advantage of negative correlation in losses between sites cause by weather patterns to create an index with lower premiums (IRI, 2009). Such patterns have been reported between Eastern and Southern African regions. In order to accurately develop a multi-site index of this nature one needs to correctly account for spatial and temporal variation in rainfall and yields of specific DTMV.

3 Model framework

Starting with a univariate framework, a spatial regression model for geo-referenced data can be specified as $Y(\mathbf{s}) = x^T(\mathbf{s})\beta + W(\mathbf{s}) + \epsilon(\mathbf{s})$. Where $Y(\mathbf{s})$ is the yield and $x(\mathbf{s})$ a p x 1 vector of predictors, both observed in locations indexed by $\mathbf{s}$; $W(\mathbf{s}) : \mathbf{s}\epsilon\mathcal{D}$ is a spatial random field, with $\mathcal{D}$ an open subset of $\mathcal{R}^d$ of dimension d. For any collection of sites $\mathcal{S} = \mathbf{s}_1, ..., \mathbf{s}_n$, $\mathbf{W} = [W(\mathbf{s}_i)]_{i=1}^n$ follow a well-defined joint distribution; $\epsilon(\mathbf{s}) \overset{\text{iid}}{\sim} N(0, \tau^2)$ is the nugget effect or error that measures micro-scale variation.

$$(1) \qquad \mathbf{Y}(\mathbf{s}) = \mathbf{X}^T(\mathbf{s})\beta + \mathbf{W}(\mathbf{s}) + \epsilon(\mathbf{s}).$$

Extending to multivariate framework as in equation (1), where $\mathbf{Y}(\mathbf{s}) = [Y_i(\mathbf{s})]_{i=1}^m$ is an m x 1 response (yield) vector and $\mathbf{X}^T(\mathbf{s}) = [x_i^T(\mathbf{s})]_{i=1}^m$ is a m x p matrix of predictors, both observed at each site, where $p = \Sigma_{i=1}^{m} p_i$. In this case, $\mathbf{W}(\mathbf{s}) = [W_i(\mathbf{s})]_{i=1}^{m}$ is an m x 1 multivariate gaussian process with mean vector zeros and an m x m cross covariance matrix $\mathbf{K}(\mathbf{s}, \mathbf{s}^{'}; \theta) = [Cov(W_i(\mathbf{s}), W_j(\mathbf{s}^{'}))]_{i,j=1}^{m}$. The $(i, j)^{th}$ represent the covariance between $W_i(\mathbf{s})$ and $W_j(\mathbf{s})$, while θ are parameters that control correlation decay process in all four (exponential, spherical, gaussian and matérn) correlation functions. If n observations are collected across $\mathcal{S}$ sites, $\mathbf{W} = [\mathbf{W}(\mathbf{s_i})]_{i=1}^{n}$, is an mn x 1 vector, is a realization of the spatial process with a multivariate normal distribution given as $\mathbf{W} \sim MVN(\mathbf{0}, \Sigma_{\mathbf{W}}(\theta))$, where $\Sigma_{\mathbf{W}}(\theta) = [\mathbf{K}(\mathbf{s_i}, \mathbf{s_j}; \theta)]_{i,j=1}^{n}$ is an mn x mn matrix with $\mathbf{K}(\mathbf{s_i}, \mathbf{s_j}; \theta)$ as the $(i, j)^{th}$ block with m x m dimension. The covariance matrix of the response sample $\mathbf{Y} = [\mathbf{Y}(\mathbf{s_i})]_{i=1}^{n} = \Sigma_{\mathbf{W}}(\theta) + I_n \otimes \Psi$, where I_n is an n x n identity matrix and $\otimes$ the kronecker product, and Ψ is an m x m cross covariance matrix between the 49 locations with τ_i^2 on the diagonal.

Estimation is only feasible when $\Sigma_{\mathbf{W}}(\theta)$ is symmetric and positive definite. Following Wackernagel (2003), we obtain feasible choices of $\Sigma_{\mathbf{W}}(\theta)$ using coregionalization whereby $\mathbf{W}(\mathbf{s})$ is linearly transformed to a more flexible form using a nonsingular spatial varying matrix ($\mathbf{A}$).

3.1 Hierarchical Bayes model

Following Gelman et al. (2003), Finley et al. (2007), and Finley et al. (2008) we employ a hierarchical Bayes approach with a generalized specification that allows the fitting of different classes of models using Gibbs sampler with Metropolis updates (Gelman et al., 2003). The generic model is specified as follows:

$$\mathbf{Y} = \mathbf{X}\beta + \mathcal{J}\hat{\mathbf{W}} + \epsilon;\ \epsilon \sim N(\mathbf{0}, I_m \otimes \Psi), \tag{2}$$

where $\mathbf{Y}$ is the mn x 1 response (yield) vector, $\mathbf{X}$ is the mn x p matrix of predictors, β is the vector of regression coefficients, $\mathcal{J} = I_n \otimes \mathbf{A}$ and $\mathcal{J}$ and $\hat{\mathbf{W}}$ are mn x mn matrices that give rise to different multivariate spatial regression models. Integrating out $\mathbf{W}$, $\mathbf{Y}$ reduces to

$MVN(\mathbf{X}\beta, \mathcal{J}\Sigma_{\hat{\mathbf{W}}}\mathcal{J}^T + I_n \otimes \Psi)$. We assume the β parameters follows a multivariate normal distribution (MVN): $\beta \sim MVN(\mu_\beta, \Sigma_\beta)$. Assuming independence in nugget effects across sites $\Psi = diag(\tau_i^2)_{i=1}^m$ with each $\tau_i^2 \sim IG(a_i, b_i)$.

The posterior distribution is then given as:

$$P(\mathbf{\Theta}|\mathbf{Data}) \propto P(\beta)P(\mathcal{J})P(\theta)P(\mathbf{\Psi})P(\mathbf{Y}|\beta, \mathcal{J}, \theta, \mathbf{\Psi}), \tag{3}$$

where $\mathbf{\Theta} = (\beta, \mathcal{J}, \theta, \mathbf{\Psi})$.

To simulate the joint posterior, the β parameters are given a diffuse multivariate normal prior, while the dispersion parameters (τ_i^2) takes on inverse gamma diffuse priors. The structure of $\mathcal{J}$ depends on $\mathbf{A}$. For stationary process, $\mathcal{J} = I_n \otimes \mathbf{A}$ and an inverse-Wishart prior is assigned on $\mathbf{A}\mathbf{A}^T$. An informative prior on decay parameters (θ) were set so that the prior means imply a spatial range of 1/4 of the maximum distance (Finley et al., 2008). Smoothness parameters (μ) for the matérn model are assumed to be uniformly distributed between 0 and 2. The Markov Chain Monte Carlo (MCMC) algorithm draws and updates β from its full conditional using Gibbs sampling, while $\mathcal{J}, \theta, \mathbf{\Psi}$ are updated using Metropolis-Hastings steps. We simulated L (10,000) samples of the joint posterior distribution and discarded the first 7500.

Then, posterior distribution of $\hat{\mathbf{W}}$ is recovered from the following posterior predictive distribution.

$$P(\hat{\mathbf{W}}|\mathbf{Data}) \propto \int P(\hat{\mathbf{W}}|\mathbf{\Theta}, \mathbf{Data})P(\mathbf{\Theta}|\mathbf{Data})d\mathbf{\Theta}. \tag{4}$$

First, we draw $(\mathbf{\Theta}^l)_{l=1}^L$ from $P(\mathbf{\Theta}|\mathbf{Data})$, and then use them in $P(\hat{\mathbf{W}}|\mathbf{\Theta}, \mathbf{Data})$ to draw $\hat{\mathbf{W}}^l$ samples of the spatial random field.

To predict yields in n^* locations, with sites $(\mathbf{s}_\diamond)_{i=1}^{n^*}$ using simulated rainfall occurrences over the growing season, we derive new spatial random fields ($\hat{\mathbf{W}}^*$) from the following predictive distribution:

$$P(\hat{\mathbf{W}}^*|\mathbf{Data}) \propto \int P(\hat{\mathbf{W}}^*|\hat{\mathbf{W}}, \mathbf{\Theta}, \mathbf{Data}) P(\hat{\mathbf{W}}|\mathbf{\Theta}, \mathbf{Data}) P(\mathbf{\Theta}|\mathbf{Data}) d\mathbf{\Theta} d\hat{\mathbf{W}}, \tag{5}$$

where $\hat{\mathbf{W}}^* = \hat{\mathbf{W}}(\mathbf{s}_\diamond)_{i=1}^{n^*}$. With these estimates, we then predict yield as $\mathbf{Y}^* = [\mathbf{Y}(\mathbf{s}_\diamond]_{i=1}^{n^*}$ using $E[\mathbf{Y}^*|\mathbf{Data}]^{(l)} = \mathbf{X}^*\beta^{(l)} + \mathcal{J}^{(l)}\hat{\mathbf{W}}^{*(l)}$. Predictions at new locations can equally be obtained in a similar manner using equation (6).

$$P(\mathbf{Y}^*|\mathbf{Data}) \propto \int P(\mathbf{Y}^*|\mathbf{\Theta}, \mathbf{Data}) P(\mathbf{\Theta}|\mathbf{Data}) d\mathbf{\Theta}. \tag{6}$$

To identify the final model, we estimated 28 separate models made up of different combination of predictors and spatial correlation functions (exponential, gaussian, spherical and matérn) and compare their deviance information criterion (DIC), effective number of parameters (pD), sum of squared error (G), deviance criterium (D) (Gneiting and Raftery, 2007) and a predictive loss function (Gelfand and Ghosh, 1998). The later criterion (D=G+P) minimizes the loss function using both a goodness-of-fit term (G=sum of squared error) and a penalty criterion (P) for adding more predictors in the model. The results for the selection process are presented in Table 1. Based on these criterion, we selected the hierarchical Bayes model with a matérn spatial correlation structure and $\mathbf{X_6}$ as the matrix of predictors. The matrix of predictors ($\mathbf{X_6}$) includes cumulative rainfall (PRCP) over the growing season and four indicator (dummy) variables for agro-mega environments taking dry lowland as the base group. Therefore $\rho(\mathbf{s_i}, \mathbf{s_j}; \theta)$ is now

$$\rho(\mathbf{s_i}, \mathbf{s_j}; \theta, \mu) = \frac{1}{2^{\mu-1}\Gamma(\mu)}(||\mathbf{s_i} - \mathbf{s_j}||\theta)^\mu \hbar_\mu(||\mathbf{s_i} - \mathbf{s_j}||\theta); \Phi > 0, \mu > 0 \tag{7}$$

where θ controls the decay in spatial correlation and μ is a smoothness parameter with higher values yielding smoother process realizations; Γ is the gamma function and $\hbar_\mu$ is a Bessel function of order μ; and $||\mathbf{s_i} - \mathbf{s_j}||$ is the Euclidean distance between site $\mathbf{s_i}$ and $\mathbf{s_j}$.[2]

Table 1 about here

We cross validate the final model by randomly selecting and excluding data from six (out of forty nine) locations and estimate the model with 43 observations. Predictions were then made for the excluded locations and the results compared with the actual yields. Plots of predicted yields versus actual yields (Figure 1) overall show good prediction of the observed yields indicating strong potential for predicting out of sample, and thus in evaluating the performance of DTMV under water stress conditions that have not been observed. Predictions in the wet upper mid altitude in Zimbabwe (Mtoko) and wet lower mid altitude in Malawi (Chipoka) appear to be much better compared to the other locations.

Figure 1 about here

Synthetic daily rainfall samples for 500 years were generated over the 49 locations using a first-order two-state markov chain (Wilks, 1998). The approach uses serially independent and spatially correlated random numbers, which are then employed individually to generate daily precipitation occurrences and amounts equivalent to time series at each site. Satellite daily rainfall data from 1983 to 2013 at a 10km by 10km spatial resolution from the National Oceanic and Atmospheric Administration (NOAA) are use in the simulation. A precipitation threshold of 0.01 inches is use to calibrate the observe daily rainfall occurrences into dry or wet state, and the markov transition probabilities are derived from direct frequency estimates of the the four states (dry-wet, dry-dry, wet-wet and wet-dry). To model the rainfall amounts, we use a two parameter gamma distribution instead of a mixed exponential distribution as in Wilks (1998). The former has been found to fit rainfall data in Africa and Middle Eastern regions better (Mhanna and Bauwens, 2012).[3] Next, we use the synthetic rainfall

[2] Covariance functions that depend only on the distance metric to model spatial correlation between points are referred to as isotropic.

[3] For more details about the step-by-step approach, see Wilks (1998) and Mhanna and Bauwens (2012). We updated and use R source codes from Mhanna and Bauwens (2012) available online to conduct our simulations.

generated to calibrate the rainfall index at each location. For simplicity and because we used a statistical and not a crop growth model to predict yields, we calibrate the index based on a single phase maize growing season.[4] The resulting index (I_{sh}) at site s with trigger h is given by

$$I_{sh} = \{1 - \frac{R_{p,s,t}}{R_{sh}}\}, \tag{8}$$

where $R_{p,s,t} = \Sigma_{t=Pd}^{Hd} r_{p,s,t}$ is the cumulative rainfall amount over the maize growing season, that is from the planting date (Pd) to Harvesting date (Hd) predicted at site s for the t^{th} time period, R_{sh} is the set cumulative rainfall trigger at site s below which indemnities are paid.[5] By using observed planting dates for each location, the index directly allows for shifting sowing windows across space making the contracts more reliable. The value of the trigger chosen determines the layer of drought risk covered and the potential complementarity with other sources of insurance. Different RII policies are obtain by varying the trigger level. The higher the trigger the more risk layers are covered including the catastrophic layer, while lower trigger levels will leave out mild to moderate risk layers which occur more frequently. Therefore complementing DTMV with RII is equivalent to finding the rainfall trigger amount such that the lower risk layer (s) are covered by the drought tolerant traits in maize variety. However, to evaluate the performance of the bundle for an index insurance based on a specific drought tolerant maize require comparing the outcome of a similar index when applied to a non/less drought tolerant maize variety (baseline).

In this study we take a general approach to investigate the potential complementarity between DTMV and the rainfall index. Specifically, we explore three rainfall triggers levels (high, medium, low indexed by h) selected to disaggregate drought risk at each location into mild, moderate and severe risk allowing a non drought tolerant, moderately drought tolerant

[4]Multi-phase weather index designed to capture the different crop growth stages and their water requirements are expected to better correlate with yields than a single phase index.

[5]Alternatively, rainfall shortfall and thus losses can be capped at a maximum by setting an exit rainfall amount. We also investigated a standardized index but it did not perform better.

and a highly drought tolerant maize to complement a RII design to insure mild, moderate and severe drought risk respectively.[6] The first (high) trigger is set at the expected cumulative rainfall over the growing season, the second (medium) is set at 0.75 standard deviation below the expected rainfall, while the third (low) is set at 1.5 standard deviation below the expected rainfall. The index insurance derive from the first trigger seeks to insure against all (mild to extreme) drought risk layers, the second insures against moderate to severe drought conditions while the third aim to cover severe to extreme drought events. We expect DTMV to perform relatively well compared to the baseline variety under mild to moderate drought conditions, thus complementing an index insurance with a lower rainfall trigger to insure households against all drought risk layers at an affordable rate. The yield loss for maize variety i (L_{ish}) mapped by the index at each site is estimated using

$$L_{ish} = Max(I_{sh}, 0)E(Y_{is}), \tag{9}$$

where $E(Y_{is})$ is the expected yield of maize variety i at site s. The corresponding actuarially fair premiums is derived as

$$P_{ish} = E(L_{ish}) + BL, \tag{10}$$

where BL is the buffer load that accounts for the extreme yield losses (tail events) thereby avoiding insurer ruin. In this study, we calculate it as the mean of the difference between indemnity and expected loss. The revenue (R_{ish}) obtain from growing variety i at site s covered with insurance that trigger at h is derived as

$$R_{ish} = \tilde{P}(y_{is} - P_{ish} + L_{ish}), \tag{11}$$

[6] An optimum trigger for each maize variety can be obtain by minimizing the variance of yield losses (Osgood et al., 2007). This can easily be obtain in this study by grid search since very few parameters are involved in the objective function.

where y_{is} is the predicted yield at site s and $\tilde{P}$ is market price or cost per unit of production. To facilitate the comparison of results across countries (with different currencies), we set $\tilde{P}$ to 1. To estimate certainty equivalent (CE_{ish}) revenue of maize variety i at site s under a contract that trigger at h, we used a constant relative risk aversion utility function $U(R_{ish}) = \frac{(R_{ish})^{1-\lambda}}{1-\lambda}$ with a risk aversion parameter (λ) of 2 based on estimates found in the literature:

$$\begin{aligned} CE_{ish} &= U^{-1}(\int U(R_{ish})f(y_{is})d(y_{ish})) \\ &= [(1-\lambda)(\frac{1}{k}\Sigma_{f=1}^{k}U(R_{ish}^{(f)}))]^{\frac{1}{(1-\lambda)}} \end{aligned} \tag{12}$$

Where $k(=500)$, is the number draws at each site. The yield differential for each site s based on an insurance with trigger h was derived as the difference in predicted yield between variety i and a site specific baseline variety. In a bit to capture the possible range of variation in the yield differential and benefits of each bundle between varieties with different degree of tolerance to drought, and due to the absence of a local maize variety in the model, the variety with the least certainty equivalent revenue ($CE_{sh,min}$) at the site was chosen as the baseline, i.e. $\Delta y_{sh} = y_{sh} - y_{sh}^{CE_{sh,min}}$. Finally, we estimate and compare correlations between the indices, yield and yield differentials.

We repeated similar analysis at the level of mega-environments to investigate the feasibility of expanding coverage of RII and the bundle with DTMV over similar agro-climatic areas. To achieve this, we aggregated the rainfall and yield data generated within each of the five mega-environments found in the area of study. From a practical stand point, these analysis will be comparable to using all the rainfall data collected from a network of meteorological stations within the mega-environments to calibrate a single index for the environment.

4 Data

Data for this study comes from on field trials conducted by CIMMYT in 49 farmer's field across eight countries in Eastern and Southeastern African countries. Twenty different drought tolerant maize varieties including hybrids, open-pollinated varieties, commercial varieties, and local varieties (simply referred here as DT1 to DT19) were tested on a farm plot at each location. Each farm represented a block in a randomized complete-block design. Twenty of the trials were conducted within five communities in Zimbabwe; eight within eight communities in Malawi; four trials each within four communities in Zambia and Uganda; three trials each within three communities in Mozambique and Ethiopia; five trials within five communities in Kenya and one trial in Tanzania. The 49 farm fields were associated with five different agro mega environments: dry lowland, dry-mid altitude, wet-lower-mid altitude, low wetland, and wet-upper-mid altitude.

One of the maize varieties tested is a local variety which varies by location making it difficult to model in a multivariate framework with the other 19 varieties. The results presented below are based on 19 varieties excluding the local variety.

Figure 2 about here

Table 2 about here

Using the planting and harvesting dates and geographical coordinates for each location, we calculated cumulative rainfall (PRCP) over the growing season using satellite daily rainfall data from NOAA made available through Columbia University. The rainfall estimates are obtained from a high gridded spatial resolution ($0.1^0 = 10km$ x $10km$) by blending gauge and satellite information. Summary results for the data and simulated rainfall across the 49 locations are presented in Tables 2 and 3 respectively.

Maize yields range from 0 t/ha for DT16 to 14.38 t/ha for DT7 while mean yields range from 3.12 t/ha for DT2 to 4.57 t/ha in DT11 with relatively high variation ranging from 1.78 t/ha to 2.62 t/ha. Cumulative precipitation over the growing season over all sites range from 176 mm to 1174 mm with a mean of 590 mm. On the other hand, the 500 simulated rainfall samples at each location range from 20mm in Bomangombe to 1307 mm in Malava with expected ranging from 109 mm in Bomangombe to 825 mm in Malava. Similarly, standard deviations for the expected rainfall range from 40 mm in Bomangombe to 137 mm in Matsinnho-Gond.

Table 3 about here

5 Results and Discussions

Posterior summary for selected parameters is presented in Table 4. The 95% credible interval for cumulative rainfall (β_{PRCP}) (and several mega-environment) indicates a high probability that the parameters are different from zero. Similarly, credible intervals for μ, θ, and Ψ show high probability of the estimates greater than zero. In the case of θ and μ, it shows high spatial correlation in yields across the locations. Credible interval estimates for θ show four distinct spatial trends for the DTMV ranging between 4.12 and 12. Those with wide range tend to have the least smooth spatial distribution based on estimates of μ. Estimates of non-spatial variance (Ψ) for each variety range from 0.24 to 2.28. Overall, cumulative rainfall, mega-environment type and spatial correlation are good predictors for DTMV yields.

Table 4 about here

5.1 *Stability of DTMV yields, net yields, and Index performance*

For illustrative purposes, Table 5 report stability analysis (expected yields-$\bar{y}_{sh}$, standard error - $s.e$ and coefficient of variation - CV_h, h=1,2,3) for the DT17 across 15 locations under three RII trigger points while table 6 reports similar results for DT17 and DT6 across all five agro-mega environments. Tables 7 and 8 report similar results for all DTMV in two agro-mega environments - dry lowland and low wetland respectively. The proportion of the simulated rainfall sample (pt_1) that falls below the trigger rainfall level is also reported.

Table 5 about here

Results show relatively high variation in the expected yields of DT17 across locations ranging from 0.02 t/ha in Bikita to 9.4 t/ha in Wakiso. On the contrary little variation exist across trigger levels. Overall, expected yields in most locations slightly decline from high to low trigger levels indicating that mean yields of DT17 are not much affected by mild to moderate drought conditions. Similar trends exist with the CV with most of the estimates less than 0.23 indicating somewhat stable dispersion of yields relative to the expected value under mild to moderate drought.

Table 6 about here

Table 7 about here

Table 8 about here

Comparing results reported in Table 6 for DT17 and DT6 also show stack differences in expected yields and CV between both varieties both across mega-environments and rainfall indices. These difference are even greater at location level revealing that mismatch in payout associated to differences in maize variety can be a major source of basis risk in RII contracts. Overall, results for all 19 maize varieties show that yields are much higher in low wetlands and wet-lower mid altitudes as expected (reflecting better rainfall conditions) and low in dry lowlands.

Contrary to results reported at locations and not surprising, the CV for DT17 (and DT6) across mega-environments are much higher compared to those in some locations indicating higher yield dispersion relative to the mean. However, in most situations the estimates decrease with decreases in trigger (corresponding to increase in drought severity) indicating lower risk exposure in mega-environments under moderate drought conditions.

Results reported in Tables 7 and 8 for all DTMV overall, show a decrease in expected yields with increases in drought severity across both mega-environments. However, yields in dry lowlands are lower and more variable compared to those in low wetlands. In addition, yield variability under increasing drought severity is higher in dry lowlands than low wetlands, and overall, the expected yield in dry lowlands sharply decreases (indicating increase in yield loss) with increases in drought severity as expected. Whereas in low wetlands, the loss in yield is minimal indicating potentially less concerns of water stress in such areas.

More interestingly, the performance of individual DTMV relative to others appears to be stable under different trigger (drought severity) levels within the same mega environment but vary across mega-environments. For example, in dry lowlands the top five DTMV (DT4, DT9, DT13, DT6 and DT8) at the high trigger level maintain their dominance at both medium (mild) and low (moderate) trigger (drought) levels. Similarly, the two least performing maize varieties at high trigger level (DT11 and DT12) remain the worst performing varieties at low trigger level. However, in dry lowlands only two of the top five varieties make the top five in low wetlands. For example DT4 (DT6) ranked as the first (fourth) in terms of expected yield in dry lowlands suddenly becomes the fourth (second) in low wetlands. These results reveal the existence of a persistence and positive correlation between the drought tolerant traits of any two maize varieties within a mega-environment under changing drought severity. This will facilitate the estimation of net yield gains between any pair of competing drought tolerant maize varieties thus making the selection and bundling of a specific drought tolerant maize variety with an index insurance in specific communities and mega-environments possible. However, efforts of scaling up across mega-environments will require creating separate bundles (by matching the right variety with the right rainfall index insurance) for each mega-environment.

To further assess the potential of bundling a drought tolerant maize with an index insurance, we examine the expected net (differential) yields ($\Delta \bar{y}_{s,h}$) between a baseline variety taken to be the one with the lowest certainty equivalent (CE), both across space and trigger levels. Note that the least valued maize base on CE can vary by location and mega-environment. We present and discuss the CE results in the next section. To examine the relationship between (net) yields and the index we estimate the correlation between the them. For illustration and comparison purposes, Table 9 reports results for DT17 across 15 locations for each trigger while Table 10 reports similar results across mega-environments for DT17 and DT6. In addition, Tables 11 and 11 present the same results for the DTMV in dry lowlands and low wetlands.

Table 9 about here

Results show high variation in net yields (ranging from -0.01 t/ha in Bikita to 6.54 t/ha in Mrewa/Alupe) between DT17 and the baseline maize variety across locations, however with little/no variation across trigger levels, further supporting earlier evidence of a persistence in (relative) drought tolerance of maize varieties. The lack of variation in net yields across triggers is due to the same variety being the baseline at all trigger levels, and since there is a defined relationship between net yields for any two varieties across trigger levels, we therefore have the same expected yields and correlation. However, this does not imply zero variation in net yields between DTMV at the same location. Only 4 of the 49 locations show a switch of a variety with lowest CE moving from high trigger level to low level. Overall, the correlation between DT17 net yields and the indices is low indicating the presence of basis risk in the insurance.

As expected with aggregated data, results depicted in Table 10 show lower variation in net yields (-0.28 to 2.31 for DT6 and -0.93 to 1.31 for DT17) across mega-environments compared to those across locations. However, there appear to be slightly higher variation in net yields across different trigger levels in mega-environments indicating that the benefits of a RII vary with the drought tolerance of the maize variety chosen as well as the layer of drought risk insured. Note that variation of net yields across trigger levels can also be due to a change in the baseline maize variety (and thus net yields) under different trigger levels.

Table 10 about here

Table 11 about here

Table 12 about here

Similarly, results from Tables 11 and 12 show relatively high variation in net yields (benefits) amongst the DTMV within and across mega-environment, however with minimal variation from one trigger level to another for a specific variety within a mega-environment. For example, in dry lowlands (low wetlands) net yields for DT6 is about 9 (1.5) times greater than that for DT3. The variation in net yields amongst all varieties is unexpectedly higher in low wetlands (-0.57 t/ha to 2.31 t/ha) than dry lowlands (-0.32 t/ha to 1.73 t/ha), and most (64 %) of the maize varieties show higher net yields in low wetlands than dry lowlands reflecting increased water stress conditions in dry lowlands compared to low wetlands. These results (especially the persistence in net yields across trigger levels for any given pair of maize varieties) reinforce the possibility of calibrating and selecting an efficient RII based on the complementarity of drought tolerance traits of a specific maize variety within a given environment.

Results reported in Tables 9, 10, 11 and 12 show that the correlation between the index and the net yield can be negative or positive depending on the variety and the environment. For a given maize variety the sign varies across locations and mega-environments but remains the same across the three trigger levels. A positive correlation indicates that net yields increase with increases in the index.[8] Thus a positive correlation indicates that net yields between the baseline maize variety and another is increasing with increase in drought.

On the contrary, a negative correlation indicates that net yields between the baseline maize variety and another is decreasing with increase in drought conditions. These results depict the existence of a quadratic relation between net yields and a rainfall index and thus supports the stylized conceptual framework in Lybbert and Carter (2014) for bundling a drought tolerant maize variety and rainfall index insurance. In this relationship, net yields between a more drought tolerant variety and a less drought tolerant one approaches zero under (near) normal rainfall conditions. As the rainfall amount decreases, the more drought

[8]Increasing the index is the same as increasing drought severity or decreasing cumulative rainfall over the growing season.

tolerant variety yields get increasingly better than the less drought tolerant variety. Beyond a certain point, yields for the more drought tolerant variety also start to decrease and so thus the net yields. For extremely severe drought condition, yields and thus net yields from both varieties become zero. Therefore, an optimal bundle between a DT (compared to a non DT) maize variety and a rainfall index can be found by selecting a trigger level at which the expected net yield (beyond the maximum) is zero. Situations where the correlation is positive suggest the maximum net yield is yet to be reached while a negative correlation suggests it is beyond the point of maximum net yield. Mindful that finding the optimum trigger point is difficult in practice, a significant negative correlation between the index and net yields can be use as a good pointer to an optimum trigger.

Overall, high negative correlation estimates (up to -0.73) are more likely in dry lowlands compared to low wetlands and specific locations, thus indicating an even higher potential of efficiently bundling a drought tolerant maize variety with an index insurance in dry lowlands.

5.2 *Potential Welfare changes from bundling DTMV and Index Insurance*

For illustrative purposes, Table 13 report estimates of premium (P_h), certainty equivalent revenue and the percentage change in CE (ΔCE) between DT17 and the variety with the least CE at the site for all three trigger levels across 15 location. Estimates of the correlation between the index and yields for DT17 with corresponding p-values ($\rho_{y_{sh}}(p.v)$) are also reported. Table 14 report similar results for DT6 and DT17 by mega-environments while Tables 15 and 16 also report the same results for all 19 DTMV within the dry lowlands and low wetlands respectively.

Table 13 about here

The results in Tables 13, 14, 15 and 16 show high variability in the RII premium and certainty equivalent (CE) estimates amongst maize varieties within and across locations and mega-environments. As expected, the premium estimates decrease with lower trigger levels indicating a decrease in the likelihood of having more severe droughts events. However, the results show that at the level of location or mega-environment, each variety can experience either an overall increase or decrease in CE and ΔCE with a decrease in trigger level from high to low, thus indicating existence of an optimum trigger level which vary with maize variety tolerance to drought, environment and the baseline maize variety. In situations in which the relative benefits decrease with a decrease in the trigger from high to low, it indicates the variety in question has exceeded its maximum benefits (tolerance to drought) relative to the baseline variety. Whereas, when relative benefits increase with a decrease in the trigger level, it indicates that the maximum benefit point relative to the baseline variety is yet to be attained.

Table 14 about here

Table 15 about here

Table 16 about here

Based on the results reported in Table 13, a RII calibrated for DT17 to insure all drought risk layers (that is with high rainfall trigger level) will be most beneficial in Mrewa ($\Delta CE =$ 167% and 232%) when compared to the baseline variety. While similar index insurances with medium and low triggers - designed not to cover mild and moderate drought risk respectively will be most beneficial in Monze ($\Delta CE = 241\%$ and 242%) when compared to the baseline variety. Irrespective of the layer of risk insured, the index insurance will be least beneficial for farmers in Bomangombe and parts of Bikita where $\Delta CE = 0\%$. Thus farmers/policy makers on average are better off with the baseline variety in these locations. Similarly, comparing DT6 and DT17 with the baseline variety within each of the five mega-environments as reported in Table 14 reveal that DT17 is more beneficial that DT6 (and the baseline variety) in dry lowlands, wet-lower-mid altitudes and wet-upper-mid altitudes while DT6 in more beneficial in dry-mid altitudes and low wetlands. The relative benefits of DT6 and DT17 are invariant with the layer of drought risk insured.

However, comparing the relative welfare benefits for all 19 DTMV in dry lowlands (Table 15) and low wetlands (Table 16) reveal that except for DT17 under a design with higher trigger level, DT10 is the most beneficial maize variety in dry lowlands and low wetlands. The least beneficial varieties in dry lowlands are DT13, DT11 and DT5 while in low wetlands is DT16. Notice that CE and ΔCE estimates are significantly higher in dry lowlands than low wetlands indicating that the (relative) benefits of DTMV compared to less/non drought tolerant ones are highest in dry lowlands as one will expect. In certain situations, the results also show that the relative benefits of DTMV in mega-environments (especially dry lowlands) are several folds higher that those obtained from a separate design at most of the locations within the mega-environments indicating strong potential for scaling up rainfall index insurance at the level of mega-environments. To an extend, this finding is supported by the high negative and significant correlation between the index and the yields in dry lowlands indicating less concern for basis risk.

6 Conclusion

Poor demand for index insurance with little potential for scalability and sustainability combined with higher vulnerability of rural households to drought has prompted consideration for improved risk management tools. In this study, we investigate the potential for bundling DTMV with a multi-site rainfall index insurance to better insure households against drought risk and facilitate scaling up and sustainability of farm risk management programs. We use on-farm trial data conducted by CIMMYT over 49 locations in Eastern and Southern Africa spanning 8 countries and 5 agro-mega environments with daily rainfall data to investigate the feasibility of such a bundle.

We find very high variation in the benefits of bundling a drought tolerant maize with a rainfall index. The performance of the bundle was found to depend on the maize tolerance to drought, the trigger level chosen, type of environment in which it is grown and the baseline maize variety to which it is compared. This implies there are benefits to some combination of DTMV and RII in a given environment based on the yield and premium cost at different trigger thresholds. The ultimate benefits of the bundle are realized by selecting an optimum trigger level conditional on the environment and the baseline maize variety. We find a well defined relationship between net yields and CE estimates when comparing benefits of a drought tolerant maize and a baseline variety, making it feasible to select the best variety and an optimum insurance. More so, the likelihood of calibrating an efficient bundle is high in mega environments (especially in dry lowlands) than smaller communities, showing good potential for scaling up programs in these environments. Overall, we find high correlation between the index, yields and net yields at both high, medium and low trigger levels in dry lowlands compared to smaller communities/locations, making basis risk less of a concern. In addition, the CE was found to increase while net CE decreases as we move from high to low trigger levels indicating that bundling DTMV with index insurance is more beneficial at higher trigger levels compared to using a less drought tolerant maize variety. The potential to bundle DTMV and RII and the benefits are significantly higher in dry lowlands than low wetlands.

The policy implications of these results are significant given that demand can be increased by systematically bundling the two technologies to produce contracts with lower premiums, and by increasing the area of coverage with a design that aim to insure all farmers within a dry lowland. In addition, our model framework can be use to recommend specific maize varieties that offer the most benefits at each location and mega-environment with or without RII, thus facilitating decision making under risk and multiple uncertainties to both farmers and policy makers.

More accurate yield predictions could be obtain by including other major input variables use in a crop growth model as covariate in our model. Developing a model that allows for the joint simulation of space-time rainfall and other variables such as evapotranspiration will make an excellent future research and will lay the ground work for possible improvements to this study. Also, selecting the insurance triggers in an optimization process as opposed to taking a general approach (as done in this study) can produce more insightful results on the variation of the benefits and performance of the bundle across space.

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