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Calibration of a multi-factor weather index to determine the trigger event of claim payments on crop micro insurance in Eastern Kenya

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A research project submitted in partial fulfillment of the requirements for the Degree of

Bachelor of Business Science Actuarial at Strathmore University

School of Finance and Applied Economics
Strathmore University
Nairobi, Kenya
November, 2015

DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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Abstract

In 2014, among the seven companies that offer agricultural insurance in Kenya, only two of the companies reported a profit. The shared characteristic between these two companies is that they both used index-based insurance. The intention of this study was to explore index based insurance through the calibration of a multi-factor weather index to be used in a crop micro insurance to determine the trigger event of claim payments. This research used linear regression, Generalized Linear Models and Value at Risk to illustrate the relationship between weather elements and claim payments. From this study we can conclude that we can illustrate the relationship between weather elements and expected crop yield, and therefore use this interaction to base claim payoff calculations. Recommendations for further research into this topic include widen the area under study to include areas with a wider scope of weather variations and to increase the number of crops under research to include those that are more sensitive to weather changes. The work presented aims to encourage more index-based programs in Kenya to help farmers manage risk in a more innovative way and help expand the insurance industry in Kenya as a whole.

1 Table of Contents

1. Problem Statement

1.1 *Background and Rationale of the Study*

1.1.1 Introduction

In line with Kenya's Vision 2030, the Insurance Regulatory Authority has been actively involved in trying to increase the current insurance penetration from the current 3.4%. One obvious way is to target the mass market which is largely comprised of the low income earners through micro insurance. Micro insurance differs from traditional insurance in its target market -low-income groups, its low premium -to ensure affordability, and its product design -tailored to meet the needs of the low income earners (Insurance Regulatory Authority, 2014).

Risk transfer approaches such as insurance have played a role in mitigating climate risk in many parts of the world. However, they have generally not been available in developing countries, where insurance markets are limited if they exist at all, and are not oriented towards the poor. A new type of insurance – index insurance – offers new opportunities for managing climate risk and its effect on agricultural output in developing countries.

Weather based index micro insurance in agriculture which underwrites a weather risk that is typically highly correlated with agricultural production losses is gaining popularity in lower income economies (Collier, Skees, & Barnett, 2009). This product essentially uses the weather risk as a proxy for the agricultural economic loss.

An increasing number of pilot programs using index insurance to manage risk have been implemented in many countries including India and Brazil. These pilot programmes have demonstrated the great potential of index insurance as a risk-management tool. They suggest that index insurance could not only provide an additional effective, market-mediated solution to promote agricultural development, but it could also make disaster relief more effective(Hazel, Anderson, Balzer, Clemensen, Hess, & Rispoli, 2010).So far no significant local programs have been established in Kenya.

This research aims to study how a weather index for determining the trigger event of crop insurance can be calibrated. This is important because a good index can account for the susceptibility of crops to weather factors during different stages of development, the biological and physiological characteristics of the crop and the properties of the soil. If a sufficient degree of correlation is established between the weather index and yield or crop quality, an agricultural producer can insure his production or quality risk by purchasing a contract that pays in the case specified weather events occur.

This research will also be important to the Kenyan insurance industry because it will enable them to escape or reduce the pitfalls caused by indemnity based agricultural insurance such as adverse selection, moral hazard and field loss assessments.

1.1.2 Historical Perspective

The concept of index insurance is not new. Proposals for this type of insurance were first articulated by Halcrow (1948) and Dandekar (1977). Area-yield insurance has been tried on a heavily subsidized basis in Canada, India, Sweden and the United States (Miranda,1991; Mishra,1996; Skees, Black and Barnett 1997). The Australian Government commissioned a feasibility study of rainfall insurance in the mid-1980s, but decided not to pursue it (Hazel, Anderson, Balzer, Clemensen, Hess, & Rispoli, 2010).

In 2002, donors began to finance the piloting of these ideas. In particular, the World Bank's

Commodity Risk Management Group (CRMG) was allocated trust funds from the Swiss and the Dutch governments to pilot weather insurance for farmers to complement its price risk management work in commodity markets.

CRMG was involved in its first index-based weather risk management transaction in India in

June 2003, the first-ever weather insurance project in the country. Since 2003 there have been several other pilots around the world, including completed pilots in Ukraine, Ethiopia, and Malawi, and upcoming pilots in Kenya, Tanzania, Thailand and Central America. Successes like the market growth in India have had significant demonstration effects and have proven that weather risk management for farmers in the developing world is possible through insurance-type instruments.

1.1.3 Technical Analysis

Weather index insurance responds to objective parameters, such as rainfall or temperature, at a defined weather station during an agreed period of time. The parameters of the insurance contract are set to correlate, as closely as possible, with the damages suffered by the policyholder. All policyholders within a defined area receive payouts based on the same contract and measurement at the same station, eliminating the need for field loss assessment.

By running a regression analysis against historical or simulated production data or simply by looking at historical financial worst and best years, available information can be used to establish the relationship between different values of a weather index and the financial loss or gain a farmer can expect.

1.1.4 Research Objectives

The aim of this study is to determine how a weather index for determining the trigger of crop insurance can be calibrated. In doing so, this study will identify most important elements to include in the index.

Additionally, it will enable an insurer to determine the cut-off values at which compensation should be paid to the farmers.

1.1.5 Research Questions

I. How can a weather index for determining the trigger of crop micro insurance be calibrated?

II. What are the important weather elements to include in such an index?

III. At what level of extreme weather is crop production affected to an extent deemed sufficient for a crop insurance claim to be paid?

1.1.6 Scope of Research

This research will focus on rainfall, temperature and sunshine as weather elements to include in modeling an index to determine the trigger event of crop micro insurance claim payments. The model is parameterized with respect to four crops grown in the Eastern Kenya region namely maize, sorghum, pigeon pea and beans. This study will look at the weather patterns from the planting to harvesting season of the respective crops and look at the impact on price of the crops up to 6 months after harvesting.

The rationale for this is that unfavorable weather will lead to low yields and increased demand thereby increasing the price of the harvested crop in the market.

A significant assumption of this research is that no other factor besides weather will influence crop yields.

2 Literature Review

2.1 *Introduction*

This chapter outlines the theoretical and conceptual underpinnings upon which the premise for this study is build. The Section 2.2 of this chapter provides a review of the literature of similar studies on weather-index based agricultural insurance and the Section 2.3 reviews literature regarding models used to describe the relationship between weather phenomena and agricultural yields.

2.2 *Literature on Weather Index Based Agricultural Insurance*

2.2.1 Traditional Risk Management Measures

Production risk is the predominant risk that affects the income of agricultural producers and agri-businesses. The most pervasive production risks, weather, impacts all aspects of the agricultural supply chain, particularly in economies based on rain-fed agriculture(United Nations, 2007).

Farmers in developing countries such as Kenya are more often than not based in rural areas and away from financial and technological advancements. The lack of access to formal risk management mechanisms for the majority of the world's smallholders means that households are forced to self-insure (i.e. drawdown on savings or assets to meet consumption needs in the event of a catastrophe) against catastrophic events. Informal risk management methods, however, often diminish the productivity of agricultural activities, and provide only limited coverage(Cole, Bastian, Vyas, Wendel, & Stein, 2012).

Usually farmers manage these risks using simple methods such as borrowing or withdrawing their children from school but they face several other constraints such as limited access to information, finance, markets and poor infrastructure e.g. irrigation or rural roads(The International Bank for Reconstruction and Development / The World Bank, 2011)

Crop insurance, especially index based insurance has seen to be the optimal solution since as early as 1948 when Halcrow (1948) mentioned it in her dissertation.

2.2.2 Advantages of Index-based Insurance

In general insurance is a great way of mitigating risk for farmers that may allow them to make riskier, more profitable investment decisions. Insurance can help household's smooth income across years, with the possibility of improving longer-term outcomes through increases in agricultural production and savings, and increased investment in education and health(Cole, Bastian, Vyas, Wendel, & Stein, 2012).

The main advantage of index-based insurance is that it helps escape or minimize the pitfalls caused by indemnity based agricultural insurance such as adverse selection, moral hazard and field loss assessments.

One key advantage of index-based insurance is that the transaction costs are lower. In theory at least, this makes index insurance financially viable for private-sector insurers and affordable to small farmers (Barrett, et al., 2007)

Index based crop insurance has a higher likelihood of resulting in profit for an insurer. Several studies support that index insurance eliminates several problems affecting indemnity based insurance. For example, Giné, Menand, Townsend, & Vickery, (2010) states that the use of an index also greatly reduces incentive problems, because the household is unlikely to have significant private information about the distribution of future rainfall shocks, and because the household cannot misreport the size of its loss.

Another advantage is that index insurance is subject to less adverse selection than traditional insurance. Index insurance requires that all insured farmers within the defined area have the same insurance payout conditions, regardless of their specific risk exposure. Hence, insurers and clients benefit from reduced adverse selection(International Fund for Agricultural Development (IFAD), 2011).

Index-based insurance also minimizes moral hazard. Farmers may have bad farming habits because they know that they have the safety net of the insurance, in the case of indemnity insurance. On the other hand, with index insurance, farmers have no ability to influence the claim, since payout is based on an independent weather parameter.

Other advantages include transparency, addresses correlated risks, operational, transaction costs and rapid payout (International Fund for Agricultural Development (IFAD), 2011).

2.2.3 Disadvantages of Index-based Insurance

Although theoretically promising, take-up of index-based products has grown only slowly. Households perceive weather risks as very serious, and existing informal risk sharing mechanisms as inadequate; yet significant barriers to adoption remain. These include liquidity constraints, limited financial literacy, and inadequate trusting the insurance provider(Cole, Bastian, Vyas, Wendel, & Stein, 2012).These factors are all positively correlated to take up of insurance.

As outlined by Collier et al., (2009), the most important risk facing index-based insurance is basis risk. Basis risk is the variability in the relationship between the value of losses as measured by the index and the value of the losses experienced on the farm. Careful insurance product design can reduce but not eliminate basis risk. Other risks include limited perils, replication, lack of weather data and lack of technical expertise(International Fund for Agricultural Development (IFAD), 2011).

Another limitation of index-based insurance is the complexity in modeling and calibration of a weather index. It is not only difficult to create but it's also hard to explain to the potential users thus having a negative effect on up take of the product.

2.2.4 Modeling the relationship between weather phenomena and agricultural yields

The calibration of weather elements to be used in a weather index for crop insurance is very important. A well-known precondition of insurability is that individual risks are independent or the covariance among risks is at least small. This however is not the case with anything to do with weather and agriculture because the success or failure of agricultural produce is dependent on various weather elements that are interdependent i.e. different combinations of weather elements having different effects. Thus, Okhrin, Odening, & Wei, (2012) found that investigating the dependence structure of unfavorable weather events is important for predicting the development of the agricultural insurance market

The core assumption underlying weather insurance is that there exists a covariate relationship between the underlying weather event and crop loss. It is argued that the underlying process of covariate risk is not simply an additive random component to the crop production function *per se*, but as a source of uncertainty on the production coefficients themselves. Weather risk enters the livelihood function first through its contribution to random yields, and second through other aspects of livelihood that can be affected such as food security, financial leverage, working capital management, and/or investment. Thus, the more flexible form of weather risk management is not necessarily tied to agricultural productivity, but household livelihood. G.

Turvey & Kong, (2008) thus argued that it is this interaction between production and farm household wellbeing that motivates weather risk as an area of study and makes weather insurance useful as an economic vehicle for rural stability

The simple approach is based on linear correlation coefficients between weather variables that are measured at different locations (weather stations). With these correlation coefficients at hand, decorrelation functions can be estimated that depict the correlation of weather variables as a function of the distance between weather stations. Examples of this approach can be found in Woodard and Garcia (2008) and Odening, Mußhoff, and Xu (2007).

3 Methodology

3.1 *Population and Sampling*

3.1.1 Time Period Selection

Defining the inputs to be used in the calibration models is a key challenge. A researcher may ask: "Do we use the last 10 years? The last 20 years? How about 50 years?" The problem is that climate is non-stationary, which is to say that the relevant mean and standard deviation evolve with time. Where the historical data indicates that the previous 10 years provides an improved estimate, this 10-year average is used. This brings us to another problem which is that historical data from the Kenya Meteorological Department is hard to find. This study used all the available data which thus went back 8 years.

3.1.2 Geographical Area

Eastern Kenya was the primary focus of the study. The region comprises 13 districts, broadly classified under arid and semiarid land types belonging to an agro-ecological zone classification of three to seven (arid and semiarid regions).The average poverty levels in eastern districts are more than 60 percent (Central Bureau of Statistics 2005). The region is characterized by a bimodal rainfall pattern, with long rains in April–May and short rains during October–November. The eastern Kenya region mostly benefits from short rains (<400 mm), which are poorly distributed but more reliable than long rains. In eastern Kenya, sorghum and pigeon pea are the major dry land crops, apart from maize and beans, in terms of area and production (FAOSTAT 2005). For this research study, five major districts (Kitui, Makueni, Mwingi, Mberre, and Embu) in eastern Kenya were selected to represent the presence of (1) local markets where seeds and grain of locally adapted crops such as pigeon pea and sorghum are traded on a regular basis, (2) the use of both traditional and modern varieties of these crops among the local farming community, and(3) the existence of seed-based intervention programs operated during regular and emergency times for major dry land cereals and legumes (Nagarajan, Audi, Jones, & Smale, 2007).After consultation with the Kenya Agro-Meteorological Department we narrowed our study to three locations- Meru, Embu and Machakos due to the presence of weather stations and availability of data.

This study will look at the weather patterns from the planting to harvesting season of the respective crops.

3.1.3 Crops selected

Four main crops were chosen for observation is maize, sorghum, pigeon pea and beans. The optimal conditions for growth of these crops are:

Crop	Optimal Conditions
Maize	Optimum conditions for maize growth are well distributed rainfall ranging between 250-1100 mm, a frost free period of 90-240 days, temperate to warm weather of (20-30°C)
Sorghum	The optimum growth requirements of sorghum plants, in order to exploit its inherit yield potential, are a deep well-drained fertile soil, a medium to good and fairly stable rainfall pattern during the growing season, temperate to warm weather (20 – 30 °C) and a frost-free period of approximately 120 to 140 days.
Pigeon Pea	Optimum temperatures for pigeon pea cultivation range from 18 to 38°C. Pigeon pea does not tolerate frost. Above 29°C, soil moisture and fertility need to be adequate. Rainfall optimum is 600-1000 mm/year. Pigeon pea is a short day plant. It is sensitive to high salinity and to water logging. It flowers well where rainfall is 1500 to

	2000 mm. On deep, well-structured soil it will grow where rainfall is 250 to 370 mm. Pigeon pea is rarely found above altitudes of 2000 m. Drained soils of reasonable water-holding capacity and with pH 5-7 are favourable for its growth.
Beans	Common beans grow within a range of temperatures of 17.5-27°C. Above 30°C flower buds are likely to fall and seeds are rarely formed at temperatures over 35°C. They are sensitive to night frost. Common beans are usually grown at altitudes between 600 - 1950 m in many tropical areas. A moderate well-distributed rainfall is required (300-400 mm per crop cycle) but dry weather during harvest is essential. Drought or water logging is harmful. Climbing cultivars will give economic yields in areas of high rainfall but the dwarf types appear to be more sensitive to high soil moisture levels. Suitable soil types range from light to moderately heavy and to peaty soils with near-neutral pH and good drainage. Common bean is susceptible to salinity.

Upon consultation with the Agro-Meteorological Department of Kenya, only maize was a viable crop to look at. This is still adequate as it is the staple food of Kenya and grown everywhere.

This study focuses on the following elements: Rainfall in Millimeters per day ,Air Temperature in Degrees Celsius (Maximum, Minimum, Wet bulb, Dry bulb, Dew point) and Sunshine duration in Hours as they seem to be the most influential in terms of crop growth and the information is readily available from the Kenya Meteorological Services Website.

3.2 *Models*

3.2.1 Linear Regression Model

This study is going to use regression to describe and evaluate the relationship between:

i. Expected Yield, Y, and the amount of rainfall, X1, temperature, X2, and level of sunshine, X3.

The y variable is assumed to be random or stochastic in some way i.e. to have a probability distribution while the x variables are assumed to have fixed non-stochastic values in repeated samples.

There are more than the stated explanatory variables that are determinants of y that will be omitted from the model thus we add a disturbance term, denoted by ε, will be added to the equation to capture the additional determinants such as other weather elements, use/disuse of farm inputs etc.(Crops,)

Therefore the equation is;

$$y = \mu + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \ldots (1)$$

This study uses this equation to calculate the optimal price range of the crops as per the optimal weather conditions i.e. per crop there are two equations showing the maximum and minimum conditions.

Thereafter the study uses Generalized Linear Models to show the relation between the crop prices and weather.

In summary, the assumed structure of a GLM can be specified as:

$$\mu_i = E(Y_i = g^{-1}(\textstyle\sum_i Xij\ \beta_i + \varepsilon_i)) \ldots (2)$$

$$Var(Y_i) = \Phi V(\mu_i)/\omega_i \ldots (3)$$

where

Y_i is the vector of responses

g(x) is the link function: a specified (invertible) function which relates the expected response to the linear combination of observed factors

X_{ij} is a matrix (the "design matrix") produced from the factors

β_j is a vector of model parameters, which is to be estimated

ξ_i is a vector of known effects or "offsets"

φ is a parameter to scale the function *V(x)*

V(x) is the variance function

ω_i is the prior weight that assigns credibility or weight to each observation

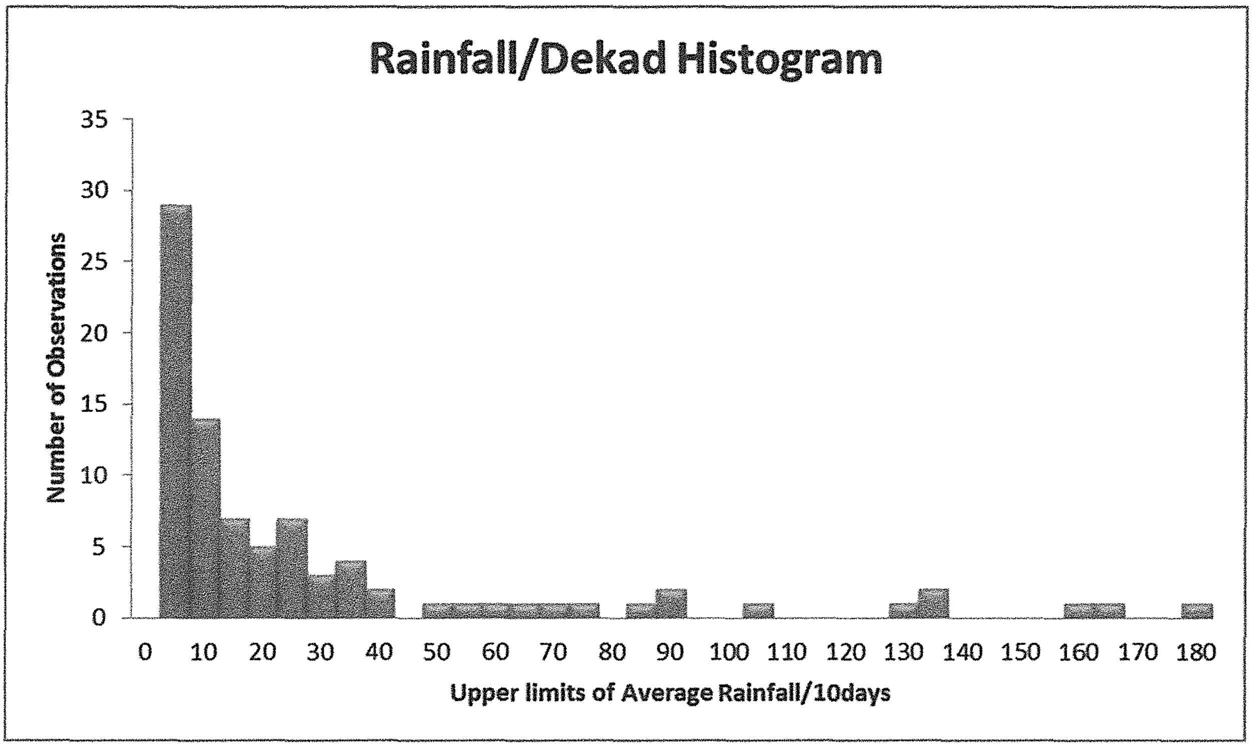
GLM's help this research to come up with the factor by factor payoffs and the multi-factor payoffs. This enables the study to find the interactions between the various weather elements effect on price and thus come up with the most important element to be calibrated in a weather index.

3.2.2 Value at Risk

In its most general form, the Value at Risk measures the potential loss in value of a risky asset or portfolio over a defined period for a given confidence interval.

This study collects historical data over the last 10 years about each of the factors (rainfall, temperature and sunshine). These values are then plotted on a histogram in order for the density functions of these factors to be identified.

These values are obtained from the Kenya Meteorological Department that publishes an analysis of weather conditions recorded at weather stations countrywide every 10days. The weather stations this study will focuses on are Meru, Embu and Machakos.



Graph 1: Rainfall Distribution in Embu from 2013-2015

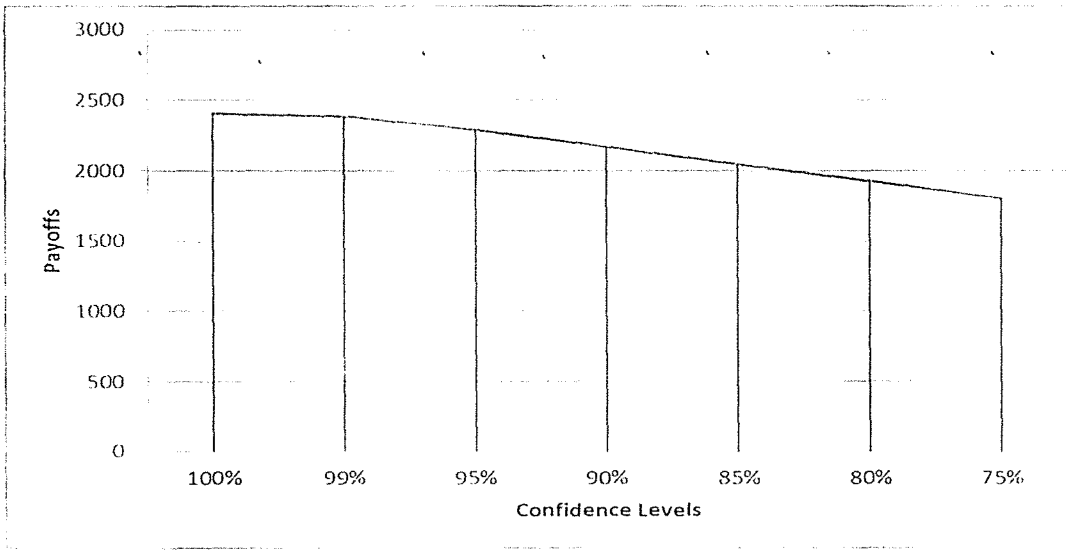
Graph 1 is a histogram illustrating distribution of rainfall as per the weather station in Embu from the beginning of 2013 to June 2015.

From there the study is able to demarcate and analyze each group in relation to optimum weather conditions for the crops and the different confidence intervals that this study will use of 99%, 95%, 90%, 80% and 75%.

For example, Kerer (2013) found that on average, Kenya is hit by one epidemic and one flooding event per year. Droughts occur on average every four years. The 150mm per Dekad mark maybe where we could demarcate our 95% VaR.(Kerer, 2013)

Using the 6-month after harvest price average of the crops this study is looking at (maize,sorghum,pigeon pea or beans) and the assumed ceiling/maximum proportion that an insurance company is willing to cover, we find the maximum payoff.

$$Maximum\ Payoff = 0.9 * AfterHarvest6monthsPriceAverage$$



Graph 2: Payoffs due as per the various Confidence Levels

Graph 2 assumes that the after harvest 6 month wholesale price of a 90kg bag of maize is Ksh.2675 (this actually the wholesale price of maize as at 2^{nd} July 2015). It illustrates the payoffs as a function of the insurance ceiling (0.9),the after harvest 6 month whole price of maize and the confidence interval.

Limitations of VAR

The first is that the approach is agnostic when it comes to distributional assumptions, and the VaR is determined by the actual movements in the risk factors. In other words, there are no underlying assumptions of normality driving the conclusion. The second is that each day in the time series carries an equal weight when it comes to measuring the VaR, a potential problem if there is a trend in the variability – lower in the earlier periods and higher in the later periods, for instance. The third is that the approach is based on the assumption of history repeating itself, with the period used providing a full and complete snapshot of the risks that the agricultural market is exposed to in other periods.

4 Results and Findings

'ntroduction

'his chapter presents the empirical findings of this study. The sections in this chapter have been ivided based on the different empirical tests that were carried out towards achieving the research bjectives of this study.

l.1 *The Relationship between Expected Yield and Weather Elements using Multi-Linear Regression Model*

'his study carried out a multi-linear regression analysis to show the relationship between the weather lements and the expected yield.
'his study aimed to look at three weather elements; rainfall, temperature and sunshine but because of ata inadequacy, only rainfall and temperature shall be analyzed for Meru and Embu, with sunshine eing added for Machakos.

he elements have been divided into first average rainfall, representing the first half of the growth age of the plant, and last average, representing the last half of the growth stage.
he expected yield is denoted by numbers 0- No yield/Not Planted, 1- Below Normal Yield, 2- Normal ield and 3- Above Normal Yield.

.1.1 The regression results

eru:

ıble 1; Regression Analysis Results for Meru showing Rainfall and Temperature

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5.422	2.069	2.620	0.040	0.359	10.485
First Av.Rainfall	-0.001	0.002	-0.628	0.553	-0.007	0.004
Last Av. Rainfall	0.016	0.005	3.493	0.013	0.005	0.028
First Av. Temp	-0.028	0.019	-1.437	0.201	-0.075	0.019
Last Av. Temp	-0.167	0.099	-1.690	0.142	-0.408	0.075

Embu:

Table 2; Regression Analysis for Embu showing Rainfall and Temperature

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.169	0.641	0.264	0.801	-1.400	1.739
First Av.Rainfall	0.007	0.003	2.351	0.057	0.000	0.014
Last Av. Rainfall	0.000	0.006	-0.017	0.987	-0.014	0.014
First Av. Temp	0.011	0.024	0.458	0.663	-0.047	0.069
Last Av. Temp	-0.002	0.030	-0.075	0.943	-0.076	0.071

Machakos:

Table 3; Regression Analysis Results for Machakos showing Rainfall, Temperature and Sunshine

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-2.914	3.315	-0.879	0.429	-12.116	6.289
First Av.Rainfall	0.040	0.033	1.238	0.283	-0.050	0.131
Last Av. Rainfall	-0.007	0.017	-0.391	0.716	-0.055	0.041
First Av. Temp	0.111	0.123	0.897	0.420	-0.232	0.453
Last Av. Temp	-0.061	0.112	-0.549	0.612	-0.371	0.248
First Av. Sun	-0.033	0.092	-0.358	0.738	-0.288	0.222
Last Av. Sun	0.057	0.109	0.526	0.627	-0.245	0.360

In statistics, the smaller the p-value, the larger the significance because it tells the investigator that the hypothesis under consideration may not adequately explain the observation. Therefore by looking at the p-values calculated we see that the expected yield is significantly affected by mostly by rainfall. This varies across the three regions but what we can consistently see is that temperature and sunshine have higher p-values of above 0.5. This shows that they are of little significance.
This is attributed to the fact that since these towns are close to the Equator the variations in temperature and sunshine are very small.

Therefore the first and last average rainfall is used to show how this index would have been carried out using two elements that are of significant importance.

Meru:

Table 4; Regression Analysis for Meru showing First Average Rainfall and Last Average Rainfall

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.380	0.376	3.671	0.006	0.513	2.246
First Av.Rainfall	-0.003	0.003	-1.147	0.284	-0.009	0.003
Last Av. Rainfall	0.014	0.006	2.542	0.035	0.001	0.028

Embu:

Table 5; Regression Analysis for Embu showing First Average Rainfall and Last Average Rainfall

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.436	0.449	0.970	0.360	-0.600	1.471
First Av.Rainfall	0.006	0.002	2.867	0.021	0.001	0.011
Last Av. Rainfall	0.000	0.005	-0.014	0.989	-0.012	0.012

Machakos:

Table 6; Regression Analysis for Machakos showing First Average Rainfall and Last Average Rainfall

	Coefficients	*Standard*	*t Stat*	*P-*	*Lower*	*Upper*

		Error		*value*	*95%*	*95%*
Intercept	1.147	0.506	2.268	0.053	-0.019	2.314
First Av.Rainfall	0.005	0.006	0.832	0.429	-0.009	0.019
Last Av. Rainfall	-0.009	0.009	-0.999	0.347	-0.029	0.012

Looking at the rainfall regressions, it is evident that the Last Average Rainfall is the most significant factor to the expected yield and therefore the index should be based on this if we were to generalize.

4.2 Measuring the Expected Loss using Simplified Value at Risk

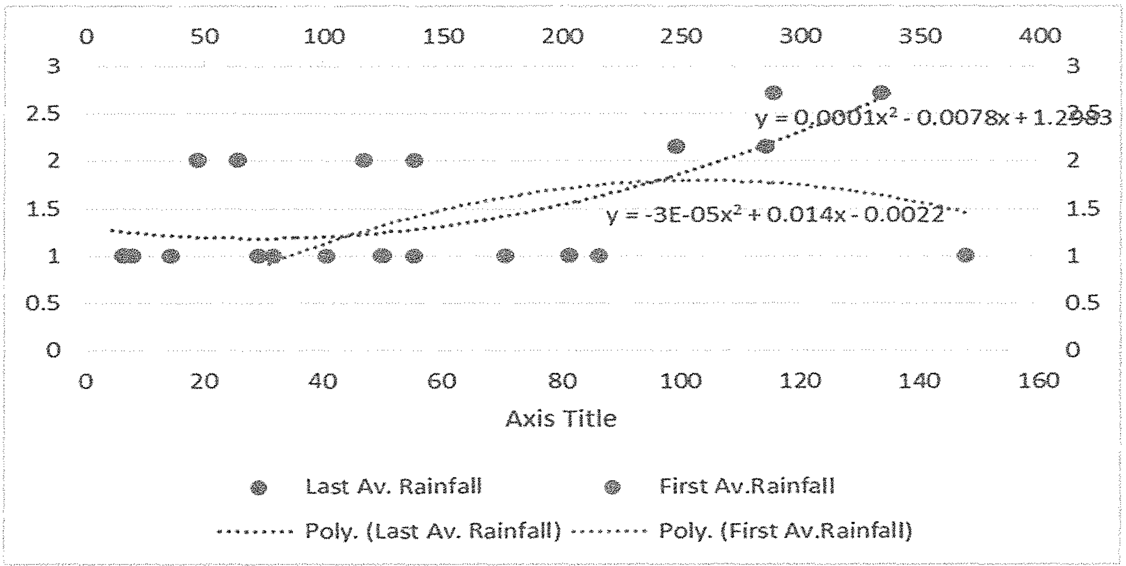
In general Value at Risk is used to measure the potential loss in value of a risky asset or portfolio over a defined period for a given confidence interval.

A simplified version of the Value at Risk is used here to show how such an index will come up with the expected payoffs.

Assuming a bag of maize would cost Kshs. 1000 and the insurer would be willing to compensate the insured up to that value of maize according to the index.

We could set the cutoff of expected yield at 1.5 i.e. one would be compensated if the expected yield is anything below that. Relating the yield to the values of the weather elements corresponding to this cutoff we get our index.

Meru:



Graph 3; Graph showing First and Last Average Rainfall against the Expected Yield

Meru P-values show that Last Rainfall is the most significant. Setting the expected yield cutoff at 1.5, we see that the insurer should pay claims when the last average rainfall is less than 200mm because this will have adverse effects on the expected yield.

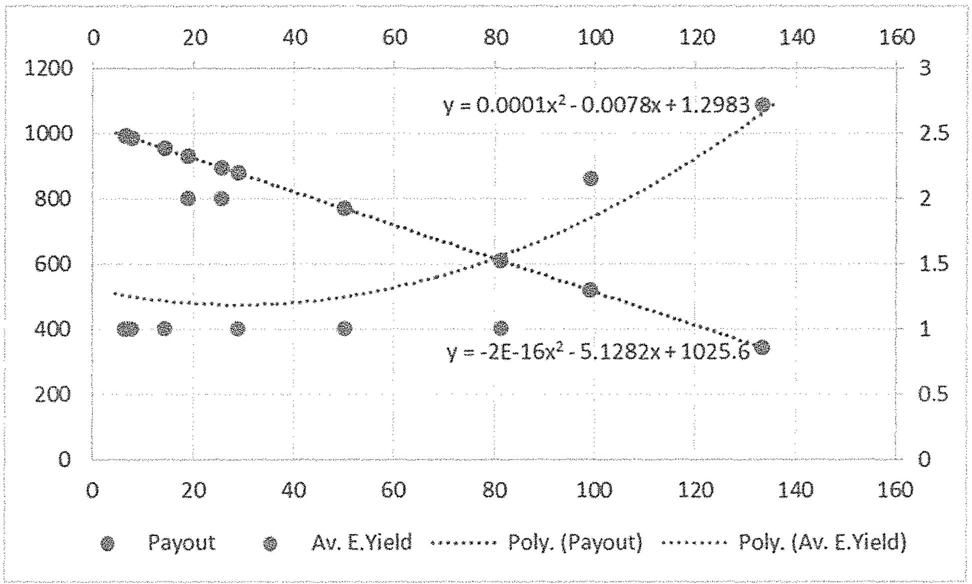
Setting the minimum last rainfall at 5mm and the maximum payoff at Kshs. 1000 a rainfall payment index is generated using the table below where the payoff is made a function of the rainfall deviation from the normal.

Table 7; Expected Yield, Last Average Rainfall, Rainfall Difference and Payout.
The last average rainfall is the most significant element to the expected yield and thus it follows that the payout is based on the difference between the last average rainfall value and the rainfall optimal conditions.

Av. E.Yield	Last Av. Rainfall	Difference	Payout
1	6.514285714	193.4857143	992.2344
1	81.4	118.6	608.2051
1	6.428571429	193.5714286	992.674
2.714285714	133.5428571	66.45714286	340.8059

2	25.64285714	174.3571429	894.1392
1	29.07142857	170.9285714	876.5568
1	14.45714286	185.5428571	951.5018
1	50.225	149.775	768.0769
2	19.05714286	180.9428571	927.9121
2.142857143	99.24285714	100.7571429	516.7033
1	7.875	192.125	985.2564

This information leads us to the graph below.

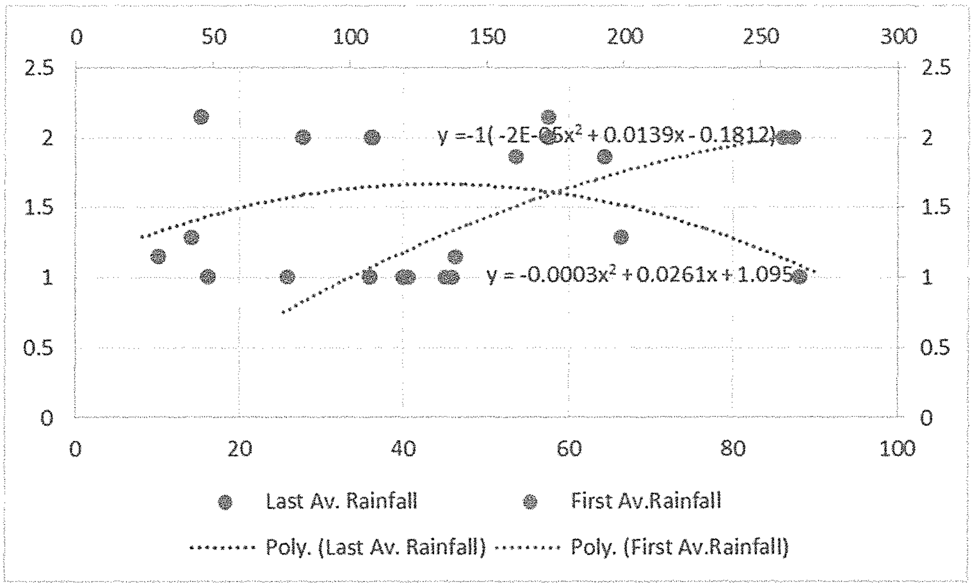


*Graph 4;*Combination graph showing the Payout and Expected Yield against the Last Average Rainfall

This clearly illustrates that the expected yield is dependent on the amount of rainfall and it therefore follows that the payoff will be a function of the rainfall.

As rainfall increases beyond a certain point, the yield decreases and thus the payoff increases. The reverse is the same.

Embu:



Graph 5; Graph showing First and Last Average Rainfall against the Expected Yield

Embu P-values show that First Average Rainfall is the most significant. Setting the expected yield cutoff at 1.5, we see that the insurer should pay claims when the last average rainfall is less than 160mm because this will have adverse effects on the expected yield.

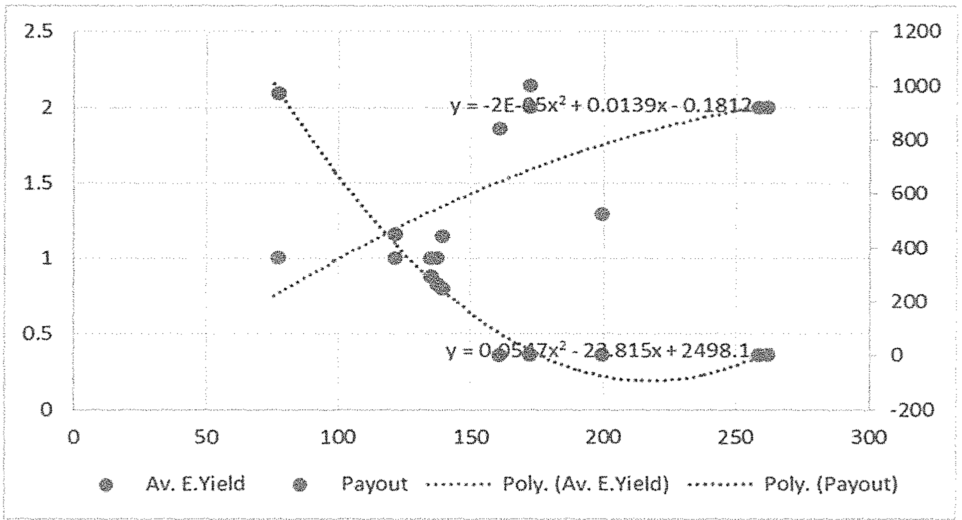
Setting the minimum last rainfall at 75mm and the maximum payoff at Kshs. 1000 a rainfall payment index can be generated using the table below where the payoff is made a function of the rainfall deviation from the normal.

Table 8; Expected Yield, First Average Rainfall, Rainfall Difference, Payout
The first average rainfall is the most significant element to the expected yield and thus it follows that the payout is based on the difference between the first average rainfall value and the rainfall optimal conditions.

Av. E.Yield	First Av.Rainfall	Difference	Payout
1	137.5625	22.4375	263.9706

1	121.6625	38.3375	451.0294
1.142857143	139.0875	20.9125	246.0294
1.857142857	161.0428571	0	0
2	172.525	0	0
1	77.72	82.28	968
2.142857143	172.525	0	0
1.285714286	199.6	0	0
2	258.3875	0	0
2	261.95	0	0
1	135.0375	24.9625	293.6765

This information leads us to the graph below.

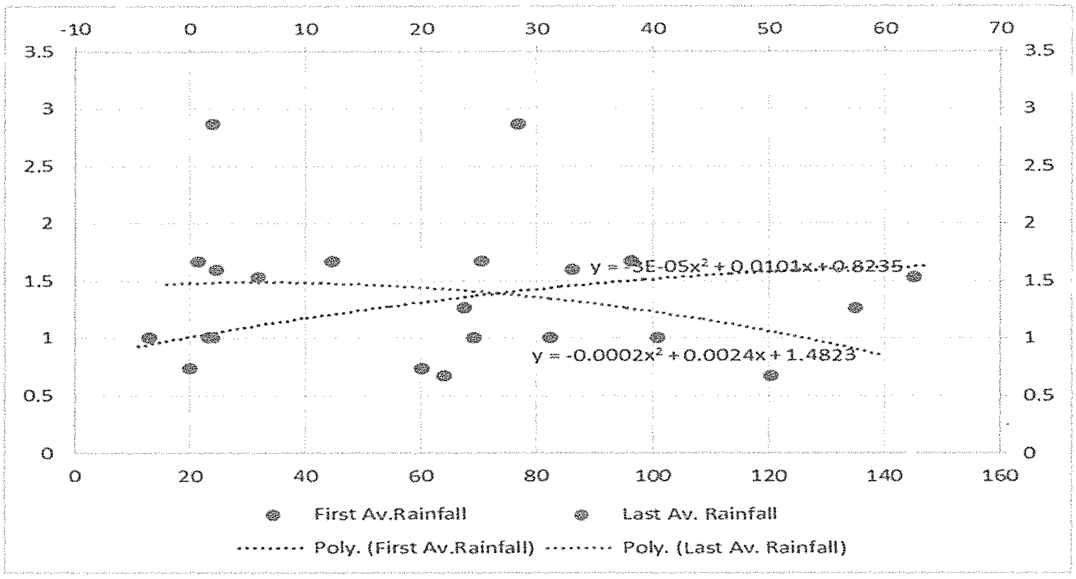


Graph 6; Combination graph showing the Payout and Expected Yield against the First Average Rainfall

This clearly illustrates that the expected yield is dependent on the amount of rainfall and it therefore follows that the payoff will be a function of the rainfall.

For Embu,as the rainfall increases beyond a certain point the yields decrease and thus the payoffs increase.

Machakos:



Graph 7; Graph showing First and Last Average Rainfall against the Expected Yield

Machakos P-values show that Last Rainfall is the most significant. Setting the expected yield cutoff at 1.5, we see that the insurer should pay claims when the last average rainfall is more than 10mm because this will have adverse effects on the expected yield.

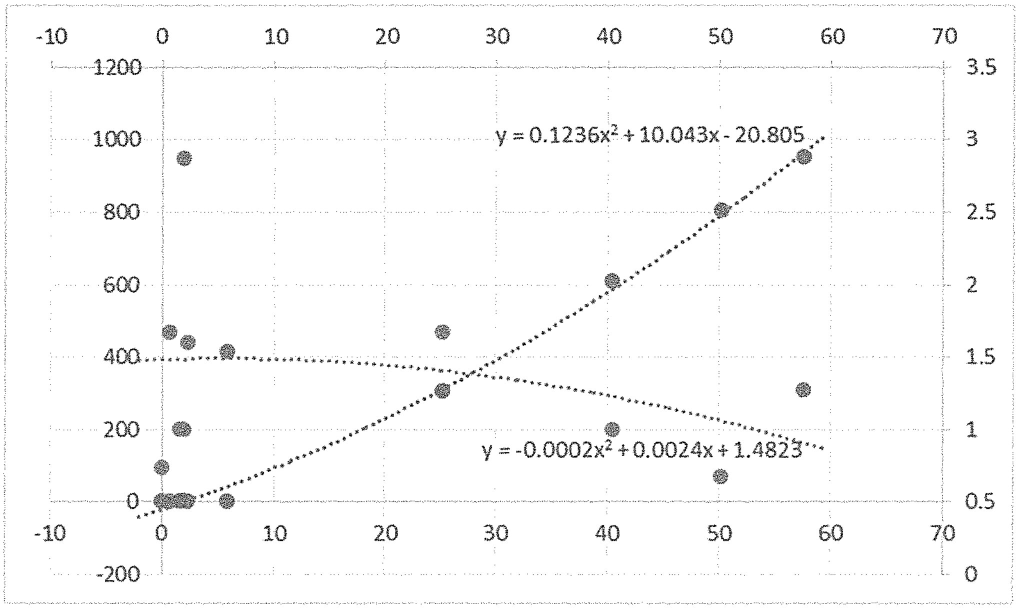
Setting the maximum last average rainfall at 50mm and the maximum payoff at Kshs. 1000 a rainfall payment index can be generated using the table below where the payoff is made a function of the rainfall deviation from the normal.

Table 9; Expected Yield, The Last Average Rainfall , Rainfall Difference, Payout.
The last average rainfall is the most significant element to the expected yield and thus it follows that the payout is based on the difference between the last average rainfall value and the rainfall optimal conditions.

Av. E.Yield	Last Av. Rainfall	Difference	Payout
1.66666667	0.75	0	0

0.66666667	50.25	40.25	805
0.73333333	0	0	0
1.26666667	57.55	47.55	951
2.86666667	2	0	0
1	40.45	30.45	609
1	2.05	0	0
1.6	2.3	0	0
1.53333333	5.9	0	0
1.66666667	25.2	15.2	304
1	1.65	0	0

This information leads us to the graph below.



*Graph 8;*Combination graph showing the Payout and Expected Yield against the Last Average Rainfall

This clearly illustrates that the expected yield is dependent on the amount of rainfall and it therefore follows that the payoff will be a function of the rainfall.

5 Summary and Conclusions

5.1 *Summary*

The purpose of this study was to explore index based insurance through the calibration of a multi-factor weather index to be used in a crop micro insurance to determine the trigger event of claim payments. This study identifies the most important elements to include in the index and determines the cut-off values at which compensation should be paid to the farmers.

To address the above objectives agro-meteorological data on maize grown in Meru, Embu and Machakos for the past 8 years was collected. This data was then taken through a multi-linear regression, generalized linear model and simplified Value at Risk to find the relationship between the expected yield and weather elements, the impact of the interaction of the weather elements on the yield and to relate all this to the payoff farmers should receive based on a developed index.

The limitations were mostly data issues such as data inadequacy, lack of data availability and poor data quality. In terms of the models used, fault could be found in that they do not take into account other factors that could affect the crop yield such as farming practices.

Further research should be done into the same topic with hopeful more data that covers a wider scope in terms of locations(locations with higher variability in weather conditions) and crops (a larger variety of crops that are more sensitive to climatic changes than the maize grown in Kenya which is a drought resistant strain).

This study is important because index-based micro insurance is seen to have a two-fold effect in that it will help farmers manage risk and to aid in the development of the insurance industry.

5.2 *Conclusion*

It is concluded that the Expected Yield in these three locations is dependent on the weather elements with rainfall in the last stages of growth being most significant. Basing an index is not only mathematically logical but will also be easy to explain to the small scale farmers that micro insurance is aimed at. There are loopholes to this analysis as it was slightly compromised by data inadequacy but it is still safe to say that the findings of this study maybe used effectively to calibrate/measure an index for weather based micro insurance in that it determined how a weather index for determining the trigger of crop insurance can be calibrated, identified most important elements to include in the index and the cut-off values at which compensation should be paid to the farmers.

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