PRICING OF WEATHER INDEX INSURANCE PRODUCTS

MUNYAKA, EMMY MWITHI

100086

Submitted in partial fulfillment of the requirements for the Degree of Bachelor of Business Science in Actuarial Science at Strathmore University

Strathmore Institute of Mathematical Sciences

Strathmore University

Nairobi, Kenya
[February, 2021]

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.

...Emmy Muithi Munyaka... [*Name of Candidate*]

.... [*Signature*]

[*Date*] 09 Feb 2021

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

...Priscillah Mogaka... [*Name of Supervisor*]

.... [*Signature*]

[*Date*] 09 Feb 2021

Strathmore Institute of Mathematical Sciences

Strathmore University

Table of Contents

ABSTRACT

Weather index insurance is relatively a new type of risk mitigation mechanism which could assist in alleviating some of the problems like moral hazard and adverse selection that are related with traditional crop insurance schemes. This paper focuses on pricing of weather index insurance products using the option pricing model, the Black-Scholes framework. Pricing of the weather index products responds to objective and independent index parameters. The index parameter is expected to have a strong correlation with the yield loss. The index parameter used in this study was rainfall and the crop yield used was maize. The rainfall data obtained from Kenya Meteorological Department and the maize yield data collected from the Ministry of Agriculture was proven to have a strong correlation. One of the assumptions of the Black-Scholes framework is that the underlying asset follows a log-normal distribution. The underlying asset in this study, rainfall, was proven to be log-normally distributed. This study focused on cases of inadequate rainfall and the payout and premium were calculated. The results show that maize farmers can protect themselves against the effects of inadequate rainfall by purchasing the weather index insurance product.

1. INTRODUCTION

1.1 Background

The agricultural sector has been a key sector in Kenya's economy for many years as it has provided a bulk of employment opportunities and has highly contributed to the economy's growth over the years. As of 2017, the agricultural sector accounted for 31.5% of GDP, 75% of the labor force and over 50% of total revenue from exports (Budget Watch, 2018/2019)

Smallholder farmers produce the majority of the agricultural output in Kenya and constitute about 80% of all the farmers. This sector is a major driver of growth in the economy, it being part of the Big Four development agenda, where the government aims to achieve 100% food and nutritional security for all Kenyans by 2022 (World Bank, 2019).

Changing weather patterns and a changing climate places the agricultural sector at risk leading to agricultural related losses through changes in frequency and severity of flood, wind, drought and other climate related events. Smallholder farmers suffer the most in the event of climate shocks. Kenya being highly dependent on rain fed agriculture and the poverty rates among smallholder farmers being too high means that it is extremely susceptible to the effects of droughts and floods.

Consequently, the severe droughts between 2008 and 2011 was one of the key contributors to the reduction in Kenya's GDP growth rate from an average of 6.5% in 2006 to an average of 3.8% between 2008 and 2012 translating to a 968.6 billion that was lost in the economy. In 2009 alone, the agriculture sector contracted by 2.7% (Government of Kenya,2018).

Agricultural production in Kenya is dominated by maize at 38.2% and it accrued by far the biggest losses measured in production value from 1980-2012, contributing to approximately one-fifth (19.8%) of total indicative losses. Compared to the other crops, maize is greatly susceptible to moisture stress as it is wholly produced under rain fed conditions. (D'Alessandro et al., 2015)

The government and other key stakeholders in the agricultural sector have developed some strategies to mitigate the negative impacts of climate change. Agricultural insurance has become an essential tool in addressing climate-induced risks that affect farmers. It includes traditional crop insurance and weather index insurance which are the most common types of crop insurance among farmers in Kenya.

Traditional crop insurance protects against crop yield losses where pay-outs are determined through a farm level loss assessment process. It has some limitations for example, issues of moral hazard and adverse selection. It also incurs high transaction costs because the insurer has to visit the insured's farm and assess the extent to which the crops have been damaged by weather. The premiums charged in traditional crop insurance are normally costly for smallholder farmers and the corresponding payouts take too long before they are settled (Daron & Stainforth, 2014). Weather index insurance is relatively a new type of risk management tool in Kenya, which could assist in alleviating some of the problems that are related with traditional crop insurance schemes. It is based on weather index parameters such as rainfall and temperature that are measured on a pre-specified period of time at a particular weather station. A pay-out is made to the farmers once the realized value of the index is more than the predetermined threshold (for example, in the case where the insurer is protecting against too much rainfall) or whenever the index is less than the threshold (for example, in the case where the insurer is protecting against too little rainfall).

Weather index insurance is used to protect against shared rather than individual risk unlike traditional crop insurance which assesses losses on a case by case basis and makes payouts based on individual client's loss realizations. It removes the subjective nature of insurance adjustments, where neither the insurer nor the insured can influence or manipulate the weather parameters like rainfall measurements which eliminates the problem of moral hazard and adverse selection that might be brought about by information asymmetry in the parties involved. Furthermore, instead of reducing effort to increase chances of compensation, farmers have an incentive to make the best farming decisions(IFAD,2010). It also works best for crops where there is a strong correlation between yield loss and one or more weather parameters.

ACRE Africa (Formerly and widely known as Kilimo Salama) is an existing weather index insurance program in Kenya which has gained popularity among farmers. The project was developed by the Syngenta Foundation for Sustainable Agriculture and was launched in 2013 as an initiative for smallholder farmers. Between 2013 and 2017, the project covered approximately

992,214 farmers in Kenya, 391,602 in Rwanda and 205,584 in Tanzania with a total insurance portfolio of 76.9 million US Dollars (Global Index Insurance Facility,2018).

While the growth in the uptake of Weather Index Insurance among farmers in the last few years has been impressive, it cannot mask the fact that till date only a small percentage of farmers have adopted it (Sibiko et al., 2018). The impacts of climate change on micro insurance schemes can be assessed from two angles; the supply-side angle which is from the point of view of the insurers and the demand side angle which is from the point of view of the policyholders (Hochrainer et al., 2008). This study will use the supply-side angle.

1.2 Problem Statement

The design of weather index insurance requires a strong correlation between one of the index parameters and the actual yield loss incurred by the farmers. The main challenge inherent in index based insurance is basis risk. This arises when there exists variation between the loss experienced by the farmer and the pay-out that is made. Basis risk can either be geographic or structural. Structural basis risk arises when weather index insurance is not suited for a particular crop while geographic basis risk arises when there is a gap between the weather station and the farm location. Basis risk can happen for reasons including: if there is not a sufficient time series of data available to create the index; if the data is at a more aggregated level than the insured area; or if the product is not well-designed. Minimizing basis risk can be done through investing in research that allows for a more accurate matching of indices to associated losses.

Index-based insurance is data driven; satellites and terrestrial meteorological station networks can provide the data relating to weather quickly and at a high frequency. Weather index insurance relies on historical data on climate patterns to guide on the design of the products. Given that the effects of climate change are increasing over time and becoming more variable, the over-dependence of historical rainfall data to guide the design of weather index products will result in premiums that misrepresent the true magnitude of climate risks.

One of the main difficulties of weather index insurance is the uncertainness that is linked with the effect of future climate trends. Insurers should incorporate the different risks of a changing climate when pricing products. To bridge this gap, this study sought to use different climate information by creating various rainfall scenarios as well as using the historical rainfall data for pricing of the weather index products.

1.3 Research Questions

1. What amount of premium should the insurers charge to the smallholder farmers under the normal climate scenario?

2. How sensitive are weather index insurance premiums to different input climate information?

3. What is the relationship between the index parameter(rainfall) and the crop yield?

1.4 Research Objectives

1. To determine the amount of premium that insurers should charge under the normal climate scenario

2. To show the sensitivity of weather index insurance premiums after incorporating different climate information.

3. To determine the extent of correlation between the index parameter(rainfall) and crop yield.

1.5 Significance of the research

The study focuses on the Kenyan population and it will be of use to the insurance companies who offer index based insurance. Insurance companies need to develop weather insurance products that are robust and that account for changing climatic conditions. In this study, multiple sources of climate information are used to demonstrate how that information will lead to sensitivity of premiums. This will present a pricing decision making tool for index insurers.

2. LITERATURE REVIEW

2.1 Introduction

There have been a number of previous studies that have been done with regard to the topic of pricing in the insurance industry, specifically, weather index insurance. In this respect, this chapter will analyze the work that different authors have done and the various methods and theories they have used to carry out their research.

Weather variability is the major reason for fluctuations in yields and this variability is exacerbated by climate change which will further have an effect on yields (Hollis et al., 2011). Africa is predicted to be greatly affected by the impacts of climate change due to its poor adaptive measures of climate variability as can be shown by the effects of current weather extremes like droughts and floods (FAO, 2007). Therefore, solutions like agricultural insurance are paramount to protect the farmers against weather related losses. Weather index insurance is a type of agricultural insurance that allows weather risks faced by farmers to be insured in developing countries where traditional indemnity based insurance may not be the best option. (IFAD, 2011)

As stated earlier, weather index insurance is preferable to traditional agricultural insurance because it addresses most of the challenges of traditional agricultural insurance like issues of moral hazard and adverse selection.

2.2 Theoretical and empirical framework

This section provides an overview of the theories that have been brought forward by different authors in analyzing the effect of climate change on weather index insurance, specifically on the pricing of the weather index products.

Black and Scholes model

Black and Scholes (1973) and Merton (1973) published a paper on the Theory of Rational Option Pricing which is the world's most widely known options pricing model in the financial industry. The Black-Scholes model requires five key inputs: the strike/exercise price of the European option, the current share price, the time to maturity, the risk-free rate and the volatility. It also makes some assumptions for example: efficient markets, which implies that market movements can't be predicted, the risk-free rate and volatility of the underlying are known and constant and that the stock prices are lognormally distributed. Also, it assumes that the stock price process is random and it follows a Geometric Brownian Motion.

However, despite the popularity and wide use of the Black-Scholes model, it has some assumptions that don't conform to reality. Volatility can be constant in the short term but cannot be constant over a longer time period. Large stock price changes tend to be followed by large price changes while small price changes tend to be followed by small price changes, a property called volatility clustering. The Black-Scholes model assumes that the options are European which can only be exercised at maturity. It does not allow for early exercise during the life of the option, an option called American, which makes it more valuable because of the flexibility. (Teneng,2011)

For the traditional Black- Scholes model, let:

P_t =Price of a European Put Option at time t

C_{t-} =Price of a European Call option at time t

S_t = Price of share at time t

K= Exercise price/ Strike price

r = risk free rate

σ = Volatility

N(x) = Cumulative normal probability

t = time in years

$$C_t = S_t N(d_1) - K e^{-r(T-t)} N(d_2)$$

$$P_t = K e^{-r(T-t)} N(-d_2) - S_t N(-d_1)$$

Where;

$$d_1 = (\ln (S_t / K) + (\mu + 1/2\, \sigma^2)(T-t)) / \sigma \sqrt{t}$$

$$d_2 = d_1 - \sigma \sqrt{t}$$

Purchasing insurance can be thought of as buying put options. A put option gives the holder the right but not the obligation to sell the underlying asset by a certain date for a certain price (Hull,2018). We can show the link between put options and weather index insurance in the following way: The option holder in the case of weather index insurance will be the farmer, the underlying asset will be the realized values of the rainfall, the strike is the predetermined threshold value for rainfall, the option seller will be the index insurers, the option premium is the weather index premiums and exercising the put option is the same as claiming. Weather insurance and weather derivatives both protect against weather related risks. Despite the similarities inherent in insurance and derivatives, there needs to be a good documented legal distinction that prevents abuse of the regulations and classification that guides derivatives and insurance (Adeyinka et al. ,2013).

(Jewson &Brix, 2005) advocated for the use of burn analysis as one of the different approaches to price weather derivatives. The burn analysis is based on calculation of the historical loss amounts/ claim amounts of the weather index products. The price is then calculated as the average of the historical loss amounts, which is an estimate of the expected loss amount plus a risk loading as the insurer would expect a reward for the risk of them having to make a payout hence the premiums would have to be higher than the expected loss amount. The second approach of pricing as studied by the authors is index modelling which involves fitting a distribution to the historical payoff that will act as a representation of the real unknown distribution of the index and estimating the parameters of the distribution so as to price the contract based on the expected value of the distribution. Both approaches however, do not take into account current information when pricing and any event that has not occurred in the past is not considered.

(Collier et al., 2009) highlighted the specific components that are considered when pricing of weather index products which is illustrated by the following equation:

$$Price = Cost\ of\ the\ Risk + Risk\ Loading\ Costs$$
$$+ Administrative\ Costs + Cost\ of\ Ready\ \text{Access}\ to\ Capital$$

The paper defines the cost of risk (pure risk) as the expected value of loss and is estimated by using historical weather data to come up with a probability distribution of the index parameter for example rainfall or temperature. Depending on how catastrophic past events have been and their consequent effect on the crop growth and the livelihood of households among many others, triggers and pay-outs are determined.

Also, the insurer has to adjust the pure risk by taking into account other costs that might be incurred when administering an insurance contract. Ambiguity loads protect the insurer in the event that the pure risk was not accurately estimated, perhaps due to insufficient data. Events that can happen irregularly such as increasing or decreasing levels of rainfall contribute to ambiguity and that lead to an increase in premiums charged. Catastrophic loads are also considered by the insurer and they are based on the fact that significant losses can arise during the early stages of an insurance policy when the reserves are not large enough to cover the losses.

Administrative costs like delivery costs, staff and office overhead must be accounted for in pricing of the weather index products.

The author lastly considers the cost of ready access to capital by the insurer which leads to an increase in premiums charged. The insurers must consider reinsurance if they offer index insurance products since weather index insurance underwrites risks that are correlated which might result in them experiencing losses.

Daron and Stainforth (2014) conducted a study on the use of Bayesian Networks to demonstrate how insurers can incorporate multiple sources of climate risks when designing insurance products and to evaluate the viability of products after using historical climate observations and simulations of future climate. The authors studied how the Bayesian Network Tool can be used to inform Weather Index Insurance pricing decisions. The research carried out sensitivity analyses to demonstrate the interrelatedness of the pricing decisions on different climate information used and the method used to incorporate climate data.

Wamai (2016) carried out a regression analysis so as to determine the trigger rainfall level. The paper set the trigger level as the level that corresponds to the long term crop yield value (y), the dependent variable. After running the regression, the trigger level(x) is calculated. The study assumed that the stop loss rainfall value which is the level of rainfall where the maximum payout is made, is a percentage of the trigger rainfall level which was set at 30%.

(Kipkorir, 2002) also examined the distribution of annual and monthly rainfall in Njemps Flats, Baringo County in Kenya. The paper mentioned that if the rainfall data did not fit a normal distribution curve, the data would be transformed to logarithmic or square root functions and then regressed to a normal distribution curve. The study concluded that the annual rainfall was normally distributed and the monthly rainfall was log-normally or square root normally distributed. Kung'u (2017) conducted descriptive analysis for monthly rainfall in Narok County and concluded that the rainfall data follows a normal distribution.

3. METHODOLOGY

3.1 Research design

The research design adopted in this study is quantitative in nature. Such a research design is suitable for this research as it incorporates numerical inputs when determining the price of weather index products. Quantitative research is based on numerical measures that are quantifiable and the purpose is to get an understanding of common relationships that are investigated at an aggregate level.

3.2 Population and sampling

The focus regions for this study are Kakamega and Embu counties in Kenya. Maize is used as the crop in this study as it is the staple food crop in Kenya and agricultural production in the country is dominated by maize. It is mainly grown in Trans Nzoia, Trans Mara, Bungoma, Uasin Gishu, Narok, Nandi and Nakuru. Maize grows well when rainfall is between 600 and 900mm. The optimum temperature for good maize yields ranges between 18°C and 30°C where high temperatures reduce the overall production. The study areas were chosen because there exists a program for livestock, maize and wheat insurance called Kenya National Agricultural Insurance Program, that was launched in 2016 and was started in Nakuru, Bungoma and Embu (World bank, 2015) indicating that there already exists a market in the study areas for suitably designed agricultural insurance products. Also, focusing on the study areas would imply that the weather index product would have risks that are spread out across the different regions because they experience different climatic conditions hence the risk would not be too much concentrated in one area.

3.3 Data collection

This study obtained data from secondary sources. The research employs time series rainfall data and maize yield data for the past 33 years (1986 to 2019). The 33year period span was chosen as it would be indicative of the recent average weather conditions in the study area and also it was sufficient duration to incorporate the range of irregular weather patterns that have occurred in the counties over the years like severe droughts. The rainfall data was obtained from Kenya

Meteorological Department and the maize yield data was obtained from the Ministry of Agriculture.

3.4 Data analysis

The data collected was analyzed using inferential statistics. Inferential statistics was used to draw conclusions on the premium rate that should be charged from the sample based on the data collected and also to determine the relationship between the variability in rainfall and maize yield levels.

3.4.1 Pricing of weather index products using Black-Scholes model

As earlier stated, weather derivatives and weather insurance have some similarities hence they can be priced the same way. A put option is said to be in the money when the price of the underlying asset is below the strike price. A cash or nothing put option is a type of a binary option that provides a predetermined payout if the price of the underlying asset is below the strike price at the option's expiration date, or no payoff when it is above the strike price.

The price of the cash or nothing put option is:

$$P_t = Q\, e^{-r*t} N(-d_2)$$

where Q is the predetermined payout when the price of the underlying asset is less than the strike price at time T and $N(-d_2)$ is the probability that the price of the underlying asset is lower than the strike price. In this study, pricing of the weather index products will be done the same way as pricing of cash or nothing put options. This was carried out by using the Black-Scholes model. The following assumptions will be made when pricing;

- The farmer is paid a lump sum (Q) when claiming.
- The index parameter, rainfall, denoted by R should follow a lognormal distribution.
- The predefined threshold in weather index insurance is R_T
- The limit for rainfall is R_L

The premium equation will be summarized as;

$$\textbf{Premium} = Q\, e^{-r*t} N(-d_2)$$

$d_1 = (\ln(R/R_T) + (r + 1/2\,\sigma^2)(T-t))/\sigma\sqrt{t}$

$d_2 = d_1 - \sigma\sqrt{t}$

Where;

$N(-d_2)$ = the probability that the index parameter (rainfall) is less than the threshold for rainfall.

r = the risk free rate of interest

3.4.2 The payout function

This study assumes that the contract only pays out once the index parameter(rainfall) is insufficient (when rainfall amount is less than the threshold amount). The payout structure for this contract will be;

$$\text{Indemnity(Q)}= \begin{cases} 0 & if\ R > R_T \\ SI * (\frac{R_T - R}{R_T - R_L}) & if\ R_L < R < R_T \\ SI & if\ R < R_L \end{cases}$$

where R is the actual realized value of rainfall, R_T is the rainfall trigger/threshold, R_L is the limit which is the minimum level of rainfall where the maximum indemnity is paid and SI is the sum insured. If the actual rainfall amount is more than the limit but less than the threshold ($R_L<R<R_T$), then the payout is proportional to the difference between the threshold and the limit. If the actual rainfall amount is more than the trigger ($R>R_T$), then no payout is made. Lastly, if the actual rainfall amount is less than the limit ($R<R_L$), the maximum indemnity is paid (the full sum insured) i.e. the insurer will assume that there was total crop failure.

3.4.3 Determining the trigger and limit rainfall values

The trigger values and the rainfall limit need to be calculated so as to determine the payout structure above. As earlier mentioned, Wamai (2016) conducted a regression analysis to determine the trigger rainfall and limit rainfall values. This study will emulate a similar approach as that used by Wamai (2016) to determine the trigger values. The y values will be the long term maize yield values in ton/ha and the x values will be the rainfall values in millimeters. The rainfall limit(R_L) is assumed to be a percentage of the trigger level (R_T). A value of 25% of the trigger value will be set as the rainfall limit because the insurer would only want to pay the total sum insured to the farmer when the rainfall values are as minimum as possible and have caused severe crop damage.

3.4.4 Climate simulations

Once the premium has been estimated under the normal climate scenario, the study will examine uniform climate scenarios where only one climate factor varies over time in the study areas. The aim of doing these simulations was to incorporate different climate information other than only relying on historical climate data when pricing of the weather index products. The research assumes changes in precipitation of -2.5%, -5%, -10% and lastly the worst case scenario of 25%. The changes in precipitation will be multiplied by the rainfall data. The premium under each climate scenario will be estimated and we will get to determine how sensitive the premiums are to the different climate information.

3.4.5 Correlation test

In order to obtain the relationship between yield levels and rainfall, this was done by carrying out a regression analysis. A linear regression was performed to determine the degree of association between rainfall and yield loss.

The correlation test is important because, for weather index insurance to work, there needs to be strong correlation between the weather parameter and the yield loss.

3.4.6 Distribution of rainfall

The underlying asset under the Black-Scholes model follows a log-normal distribution. In this study, the underlying asset is the actual realized values of rainfall and for it to be appropriate to be used in BSM, it needs to follow a log-normal distribution. To determine the distribution of rainfall, this study transformed the rainfall values to logarithmic values and normality tests are carried out to determine if the rainfall data distribution is log-normal.

The Shapiro-Wilk test carried out proves that the rainfall data follows a log-normal distribution.

The hypothesis tests are:

H_0=The natural logarithm rainfall data follows a normal distribution

H_1=The natural logarithm rainfall data does not follow a normal distribution

Embu Shapiro-Wilk normality test

data: Embu_original$`ln(avg rainfall)`
W = 0.87766, p-value = 0.08181

The P-Value from the result is greater than 0.05 hence the null hypothesis holds. We conclude that the logarithm rainfall data follows a normal distribution implying that the rainfall data follows a log-normal distribution and hence it can be used as an appropriate index in the Black-Scholes model.

4. DATA ANALYSIS

4.1 Correlation analysis

The correlation between rainfall and maize yield values is determined because as a pre-condition for weather index insurance, the two variables need to be correlated for it to work. A regression analysis for the 2 counties was used and the results are shown below:

EMBU SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.50213
R Square	0.252135
Adjusted R Square	0.228764
Standard Error	0.265863
Observations	34

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.76256	0.76256	10.78846	0.002478
Residual	32	2.261852	0.070683		
Total	33	3.024412			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.339452	0.196616	1.726473	0.093906	-0.06104	0.739945	-0.06104	0.739945
X Variable 1	0.006014	0.001831	3.284579	0.002478	0.002284	0.009744	0.002284	0.009744

The hypothesis tests are:

H_0= Rainfall and maize yields are not correlated

H_1=Rainfall and maize yields are correlated

The p-value is 0.002478 which is less than the 5% significance level hence the null hypothesis is rejected. This signifies that the rainfall and the maize yield values from Embu county have a linear relationship, therefore can be used when pricing of the weather-index products.

KAKAMEGA SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.672082
R Square	0.451694
Adjusted R Square	0.396864
Standard Error	0.280037
Observations	12

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.646031	0.646031	8.238003	0.016663
Residual	10	0.784208	0.078421		
Total	11	1.430239			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.475999	0.686175	0.693699	0.503666	-1.05289	2.004891	-1.05289	2.004891
X Variable 1	0.011287	0.003932	2.870192	0.016663	0.002525	0.020049	0.002525	0.020049

The p-value is 0.016663 which is less than the 5% significance level hence the null hypothesis is rejected. This signifies that the rainfall and the maize yield values from Kakamega county have a linear relationship, therefore can be used when pricing of the weather-index products.

4.2 Embu County

4.2.1 The payout function

As earlier stated, the trigger value(R_T) and the rainfall(R_L) need to be calculated in order to get the payout function. Regression analysis is used to determine R_T and R_L where R_T, the x variable(rainfall), is calculated by substituting the y value as the long term average value for maize yield. The regression output above will be used to determine the values. The long term average value for maize yield is 0.967647 ton/ha, and by using the regression coefficients, the R_T is calculated to be 102.31 mm and the limit value is set to be 25% of R_T which is 25.58 mm. Assuming that the weather index product pays out Ksh1000, the payout function after substituting the values is:

$$\text{Indemnity(Q)}=\begin{cases} 0 & if\ R > 102.31 \\ 1000 * \left(\frac{102.31-R}{102.31-25.58}\right) & if\ 25.58 < R < 102.31 \\ 1000 & if\ R < 25.58 \end{cases}$$

4.2.2 Calculation of the premium

Table 1: Embu 2019 rainfall data

2019	Rainfall values(mm)
January	46.3
February	21.6
March	22.4
April	194.9
May	141.5
June	23.5
July	3.7
August	16.4
September	11.6
October	442.9
November	259.8
December	214

The following assumptions were made when determining the price of the weather-index product;

Risk-free rate, r =5%

Time=1 year

Sum insured(Ksh)=1000

R= 67.07mm

R_T=102.31mm

The actual rainfall value(R) was picked from the recent rainfall experienced from March to August because most rain is needed around that period for optimal growing of the maize crop.

μ and σ are the parameters from the log-normally distributed rainfall data. The values are 3.76 and 0.94418 respectively.

$Q\ e^{-r*t}\ N(-d_2)$

$d_1 = (\ln (R/R_T) + (\mu + 1/2\ \sigma^2)(T-t))/\ \sigma \sqrt{t}$

$d_2 = d_1 - \sigma \sqrt{t}$

$$d_1 = \frac{\ln(67.07/102.31)+(3.76+1/2*0.944162\text{^}2)*1}{0.94416*\sqrt{1}}$$

$d_1=4.007$

$d_2=4.007-0.94418$

$d_2=3.06282$

N (-3.06282) =0.00111

Indemnity (Q)= $1000*(\frac{102.31-67.07}{102.31-25.58})$

Q=459.31

Premium= 459.31*exp (-0.05) *0.001

Premium=Ksh 0.4850

4.2.3 Climate simulations

In order to account for the possibility of different climate information, this study assumed a uniform climate scenario where only one climate factor changes(precipitation) over time. The research assumes changes in precipitation of -2.5%, -5%, -10% and lastly the worst case scenario of -25%. The rainfall values under each scenario are calculated by multiplying the rainfall by the assumed decrease in precipitation. The premium amount under each scenario is calculated and the results are presented below;

Climate scenario	Premium (Ksh)	% Change in premium
2.5% decrease in precipitation	0.599588184	37%
5% decrease in precipitation	0.736869529	69%
10% decrease in precipitation	1.175331787	169%
25% decrease in precipitation	2.237362766	412%

4.3 Kakamega county

4.3.1 The payout function

The long term average value for maize yield is 2.43 ton/ha, and by using the regression coefficients, the R_T is calculated to be 273.12 mm and the limit value is set to be 25% of R_T which is 43.28 mm.

$$\text{Indemnity} = \begin{cases} 0 & if\ R > 273.12 \\ 1000 * \left(\frac{273.12 - R}{273.12 - 43.28}\right) & if\ 43.28 < R < 273.12 \\ 1000 & if\ R < 43.28 \end{cases}$$

4.3.2 Calculation of the premium

Table 2: Kakamega 2019 rainfall data

2019	Normal Rainfall values(mm)
January	22.9
February	47.3
March	63.5
April	252
May	337.7
June	300.2
July	178.5
August	222.3
September	217.6
October	342.4
November	201.9
December	279.7

The following assumptions were made when determining the price of the weather-index product;

Risk-free rate, r =5%

Time=1 year

Sum insured(Ksh)=1000

R= 225.7mm

R_T=273.12mm

μ and σ are the parameters from the log-normally distributed rainfall data. The values are 5.33 and 0.412 respectively.

$$Q\, e^{-r*t}\, N(-d_2)$$

$$d_1 = (\ln (R/ R_T) + (\mu + 1/2\, \sigma^2)\, (T-t))/ \sigma \sqrt{t}$$

$$d_2 = d_1 - \sigma \sqrt{t}$$

$$d_1 = \frac{\ln(225.7/273.12)+(5.33+1/2*0.412^2)*1}{0.412*\sqrt{1}}$$

d_1=12.664

d_2=12.664-0.412

d_2=12.2512

N (-12.2512) =0.001

$$\text{Indemnity (Q)= } 1000*(\frac{273.12-225.7}{273.12-43.28})$$

Q=206.32

Premium= 206.32*exp (-0.05) *0.001

Premium=Ksh 0.2178

4.3.3 Climate simulations

The premium amount under each scenario is calculated and the results are presented below;

Climate scenario	Premium	% Change in premium
Normal scenario	0.217843292	
2.5% decrease in precipitation	0.287685959	32%
5% decrease in precipitation	0.37415838	72%
10% decrease in precipitation	0.654642348	201%
25% decrease in precipitation	3.199950849	1369%

5. CONCLUSION

The aim of this paper was to determine the amount of premium that should be charged to the farmers. The study found that there was strong correlation between maize yield and rainfall values in Embu and Kakamega hence the pricing of weather index products was done using the Black-Scholes model.

The study incorporated the use of different climate scenarios in order to determine the effect that climate change has on premiums charged. The study examined only cases of insufficient rainfall therefore the climate scenarios that were assumed were all decreases in precipitation. For Embu, under the normal climate scenario, the premium that was determined was Ksh 0.485. A slight decrease in rainfall by 2.5% causes an increase in premiums by 37% while decreases in rainfall by 5%, 10% and 25% causes an increase in premiums by 69%, 169% and 412% respectively. For Kakamega, under the normal climate scenario, the premium that was determined was Ksh 0.218. A slight decrease in rainfall by 2.5% causes an increase in premiums by 32% while decreases in rainfall by 5%, 10% and 25% causes an increase in premiums by 72%, 201% and 1369% respectively. Insurers respond to an increase in weather risk by increasing premiums but that might in turn affect their marketability of the weather index products.

The study also established that the threshold value of rainfall and the indemnity structure have a big effect on pricing of the product. Designing of weather index products is technically challenging therefore insurers need to invest in research so as to successfully capture the relationship between the index parameter and crop yield loss.

6.REFERENCES

ACRE/Syngenta Foundation for Sustainable Agriculture—Kenya, Rwanda, Tanzania. (2018). *Global Index Insurance Project.*

Adeyinka, A. A., Krishnamurti, C., Maraseni, T., & Chantarat, S. (2013). *Viability of weather index insurance in managing drought risk in Australia.* 1–38

Collier, B., Skees, J., & Barnett, B. (2009). Weather Index Insurance and Climate Change: Opportunities and Challenges in Lower Income Countries. *The Geneva Papers on Risk and Insurance - Issues and Practice, 34*, 401–424

D'Alessandro, S. P., Caballero, J., Lichte, J., & Simpkin, S. (2015). *Agricultural Sector Risk Assessment. 138.*

Daron, J. D., & Stainforth, D. A. (2014). *Assessing pricing assumptions for weather index insurance in a changing climate. Climate Risk Management*, 1, 76–91.

Eye on the Big Four: Budget Watch for 2018/19 and the Medium Term.

Government of Kenya (2018). *National Climate Change Action Plan (Kenya) 2018-2022.* Ministry of Environment and Forestry, Nairobi, Kenya.

Hochrainer, S., Mechler, R., Pflug, G., & Lotsch, A. (2008). *Investigating the Impact of climate change on the robustness of index-based micro insurance in Malawi* (No. WPS4631; pp. 1–25). The World Bank.

Hollis, A., Day, K. A., Keenan, T. D., Cleugh, H., & Centre for Australian Weather and Climate Research. (2011). *Climate science update: A report to the 2011 Garnaut review.* The Centre for Australian Weather and Climate Research.

IFAD. (2011). *Weather Index-Based Insurance for Agricultural Development.* Rome, Italy: International Fund for Agricultural Development (IFAD).

International Fund for Agricultural Development (IFAD). (2010). *The Potential for Scale and Sustainability in Weather Index Insurance for Agriculture and Rural Livelihoods | World Food Programme.*

Jewson, S., & Brix, A. (2005). *Weather Derivative Valuation: The Meteorological, Statistical, Financial and Mathematical Foundations.* Cambridge University Press.

Kenya Economic Update. (2019) Transforming Agricultural Productivity to Achieve Food Security for All.

Kipkorir, E. C. (2002). Analysis of rainfall climate on the Njemps Flats, Baringo District, Kenya. *Journal of Arid Environments, 50*(3), 445–458.

Kung'u, R. W. (2018). *Pricing of climate change catastrophe bonds in Kenya.*

Merton, R. (1973). Rational theory of option pricing. *Bell Journal of Economics*, 4, 141–183.

Hull, J. (2018). *Options, futures, and other derivatives.* Boston: Pearson Education Limited.

Sibiko, K. W., Veettil, P. C., & Qaim, M. (2018). Small farmers' preferences for weather index insurance: Insights from Kenya. *Agriculture & Food Security, 7*(1), 53.

Teneng, D. (2011). Limitations of the Black-Scholes model. *International Research Journal of Finance and Economics*, 99–102.

Wamai, D. W. (2017). *The effect of climate change on the pricing of weather index-based crop insurance in Kenya.*

World Bank Group. 2015. *Kenya Toward a National Crop and Livestock Insurance*