Is Weather Index Insurance Sufficient for Smallholder Protection? Emerging Insights from Rainfall-Index Calibration of Maize Crop Losses in Central-West Nigeria

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Abstract

Residual impacts from rainfall deficit and failures of traditional crop insurance to protect smallholders are resulting in economic losses threatening Post-Paris adaptation target in Nigeria. Weather index insurance is being considered as a possible pathway towards sharing farmers' risks. This paper analysed reliability of rainfall indexes as proxy for calibrating grain crop losses in designing index-based insurance product for farmers in Central-West Nigeria. Results reveal that two strongest correlated rainfall indexes in the development phase of maize are the second dekad cumulative rainfall climatology and cumulative rainfall below the pre-set 440mm threshold, however it was the third dekad cumulative rainfall climatology and consecutive dry days of total rainfall < daily 2.5 mm threshold in the reproductive stage. There is an overall weak statistical relationship between maize yield and rainfall indexes calibrated in middle savannah belt of Nigeria. This study provides a firsthand empirical validation that rainfall-based indexes are though fairly promising but not sufficiently measure actual farmers' income losses, hence should not be regarded as a standalone safety-net for protecting smallholders. Careful consideration is required in developing appropriate weather indexes for designing index-based insurance product that will fully captured food crop losses significantly attributed to rainfall deficits, thus facilitate uptake in the semi-arid savannah zone of Nigeria.

Key words: rainfall deficit; agricultural losses; weather-index insurance; correlation indexes; Nigeria

Résumé

Les impacts résiduels du déficit pluviométrique et les défaillances de l'assurance-récolte traditionnelle pour protéger les petits exploitants se traduisent par des pertes économiques menaçant l'objectif d'adaptation post-Paris au Nigéria. L'assurance indicielle météorologique est considérée comme une voie possible vers le partage des risques des agriculteurs. Cet article a analysé la fiabilité des indices de précipitations comme indicateur indirect de l'étalonnage des pertes de récolte de céréales dans la conception d'un produit d'assurance basé sur un indice pour les agriculteurs du centre-ouest du Nigéria. Les résultats révèlent les deux indices de précipitations corrélés les plus forts dans la phase de développement du maïs sont la deuxième climatologie cumulative des précipitations à la décade et les précipitations cumulées en dessous du seuil prédéfini de 440 mm, mais il s'agissait de la troisième climatologie cumulative des précipitations à la décade et des journées sèches consécutives de précipitations totales <2,5 mm par jour seuil de reproduction. Il existe une relation statistique globalement faible entre le rendement du maïs et les indices de précipitations calibrés dans la ceinture de savane moyenne du Nigéria. Cette étude fournit une validation empirique de première main que les indices fondés sur les précipitations sont assez prometteurs mais ne mesurent pas suffisamment les pertes de revenus réelles des agriculteurs, et ne devraient donc pas être considérés comme un filet de sécurité autonome pour protéger les petits exploitants. Une attention particulière est requise dans l'élaboration d'indices météorologiques appropriés pour la conception de produits d'assurance basés sur des indices qui captureront pleinement les pertes de cultures vivrières attribuées de manière significative aux déficits pluviométriques et facilitant ainsi l'adoption dans la zone de savane semi-aride du Nigéria.

Mot clés: déficit pluviométrique; pertes agricoles; assurance contre les intempéries; indices de corrélation; Nigeria.

Introduction

The Fifth Assessment Report (AR5) stated that climate change is expected to have social, economic and political impacts on African society especially the Sub-Sahara, arising from the increasing harsh tropical environment. Drought is the most impactful hazard which had affected 80% uninsured African smallholders and 40% of total economic damages which illustrates the need to identify processes, methods and tools which may assist African economies to adapt on local scale (Intergovernmental Panel on Climate Change [IPCC] 2014).

Of particular concern are the income and livelihoods of low-income farmers in areas where long dry spells and rainfall uncertainties are primary sources of risk. A central problem is the huge possibility of droughts and dry spells trapping smallholders in poverty. To escape from the poverty traps, smallholders need financial cover, driven by risk assessment and local needs (International Institute for Applied Systems Analysis [IIASA] 2015). Given that global food stability may be at risk because of short-term variability in supply, evidence concludes for the need for considerable investment in adaptation actions toward a "climate-smart food system", more resilient to climate change influences on food security (Wheeler and Braun, 2013).

As stated in the National Adaptation Strategy and Plan of Action on Climate Change for Nigeria (NASPA-CCN), current and future climate changes will interfere with its ability to achieve the Vision 20: 2020 in longer term (Federal Ministry of Environment [FMoE] 2003). Converging results from climate model simulations projected that temperature will rise with an average of 1–2°C by 2050, water stress will increase by 10% and water availability will be uncertain over one-third of Nigeria's surface with consequences for food security (Building Nigeria's Response to Climate Change [BNRCC] 2011).

In 2010, an estimated 46.3% of the adult Nigerians were financially excluded. Of this estimate, 80.4% of the excluded populations live in rural areas, thus expensive to access financial services and limiting potential profits of financial institutions (Central Bank of Nigeria [CBN], 2014a). Despite that the agriculture determines over 70% of income employments and rural livelihoods and responsible for 42% share of the nation's GDP, yet the banking sector provides only 2% of its total lending to the Sector. Absence of insurance deters smallholder farmers from seeking loans for fear of default and losing productive assets secured as collateral (CBN 2014a; 2014b). In order to break this cycle, risk transfer tools such as agricultural insurance are been considered.

Several studies have been conducted to evaluate effectiveness of weather index insurance as a risk management tool. In countries where uptake has occurred, impacts have been positive but there has been a very low uptake. As a strategy of sustainable scaling-up uptake, the first-order importance of reducing basis risk, and further insights on the determinants of behaviour toward risk and insurance become more necessary (Carter, de Janvry, Sadoulet, and Alexander, 2014).

In Nigeria, it is a challenge for the climate adaptation community to find risk-financing instruments to correct the failures of existing in traditional crop insurance systems. The development of reliable future scenarios and appropriate adaptation constitute an eminent task for science, policy, and stakeholders to develop tools that minimize losses and maximize rural resilience in Nigeria (Awolala 2016). There is no known empirical study which has analysed the extent of reliability of weather indexes as proxy in estimating actual crop losses in Nigeria.

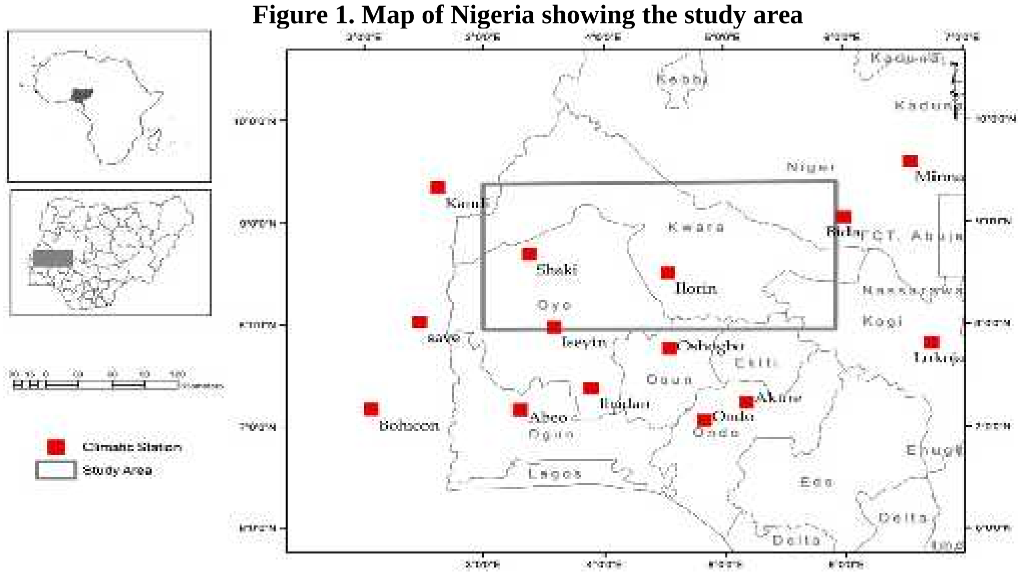
Few policy research questions thus remain that do dry spells justify weather index-based insurance design in the middle belt? Could basis risk be possibly minimized through correlated indexes for insurance contracts? The focus of this paper is to fill this research gap. This study analyzed patterns of rainfall distribution and determining extent of correlations with agricultural income losses as a critical starting point for rainfall-index insurance for drought risk-transfer in Nigeria. The study further tested if there is significant trend pattern in annual cumulative rainfall over the study area; if no statistical pattern with theoretical probability distributions, and if no positive serial correlation in the residual errors of yield and indexes, that is, ϵi have mean zero and constant variance [E(ei) = 0, Var(ei) = σ2, and E(ϵi, ϵj) = 0], (H_0 : ρ = 0 but H_a : ρ > 0).

1. Data and methodology

1.1.Study area, data and data collection

The study was carried out in the savannah middle-belt of Central-West Nigeria. The middle-belt of Nigeria is the most extensive agro-ecological zone, covering nearly 50% of the country's land surface area. Guinea savannah is the most luxuriant of the savannah vegetation belts in Nigeria (Sowunmi and Akintola 2010). The dataset used was a cross-sectional data collected from 264 peasant farmers in 2014 household surveyed across 12 different villages known for heavy concentration of maize production and within 20 km distance from nearest weather stations in the savannah belt. The 30-year decadal daily weather data (1981-2013) on rainfall were obtained from the Nigerian Meteorological Agency (NIMET), Abuja, Nigeria. Figure 1 presents the map showing the study area covering about 40,000 km^2 in Central-West Nigeria.

Figure 1. Map of Nigeria showing the study area



Source: Authors (2016)

2 Data analysis

2.1 Determination of rainfall regime from probabilistic models

The pattern of rainfall regime that best describes the decadal rainfall distribution (1984 and 2013) was determined based on theoretical distributions. Eight probabilistic functions were fitted for annual and seasonal rainfall data using Maximum Likelihood Method (MLE) to evaluate the best fit probability distribution. The description of various probabilistic models and density function, range and the parameter involved are presented in Table 1.

2.2 Construction of weather indexes

The reliability of rainfall data for the savannah AEZ for weather index insurance was obtained through a set of weather indexes tested for their correlations with maize yield to determine the most accurate indexes that best predicts yield losses at different times of the season. The causal-effect relationship between historical maize yield and selected rainfall indexes were fitted from 15 selected rainfall indexes using linear equation as shown in Table 2. Pearson correlation coefficient was used as basis for index selection at 5% level of statistical significance. The linear regression function is expressed as:

$$y \sim\sim + \quad X_i + \in_i \quad \ldots\ldots\ldots\ldots\ldots \text{(1)}$$

where,

Y_i = Annual maize yield (kg/ha); X_i = weather index in a year, *i;* ~ = intercept *(Y value when X=0)*

β = the gradient of the regression line; $£_i$ = stochastic error

Table 1. Description of rainfall probabilistic model functions

Distribution	Probability distribution function	Range	Parameters
Erlang	$f(x;k,ª) = \frac{ª^k x^{k-1} e^{-ªx}}{(k-1)!}$ for x, λ ≥ 0	$0 \le x < +\infty$	k = shape parameter (k >0) μ = scale parameter (μ = $\frac{1}{ª}$ > 0)
Exponential	$f(x;ª) = \begin{cases} ªe^{-ªx} & x \ge 0, \\ 0 & x < 0. \end{cases}$	$0 > x < +\infty$	λ = shape parameter (λ > 0)
Frechet	$\Pr(X \le x) = e^{-x^{-\sim}}$ if $x > 0$	$0 < x < +\infty$	α = shape parameter (α > 0) β = scale parameter (β > 0)
Gamma	$f(x) = \frac{(x)^{\sim -1}}{\tilde{}\,\Gamma(\sim)} \exp\left(-{(x)}\big/\right)$	$¥ \le x < +\infty$	σ = shape parameter (σ > 0) β = scale parameter (β > 0) γ = location parameter (γ = 0) *becomes the two parameter weibull distribution*
Inverse Gaussian	$f(x;«,ª) = \left[\frac{ª}{2®x^3}\right]^{1/2} \exp\frac{-ª(x-«)}{2«^2 x}$	$ª \ge x < +\infty$	μ = scale parameter (μ > 0) γ = location parameter (γ > 0)
Log-Gamma (2P)	$f(x) = \frac{(In(x))^{\sim -1}}{x \;\tilde{}\,\Gamma(\sim)} \exp\left(-In(x)\big/\right)$	$0 < x < +\infty$	α = shape parameter (α > 0) β = scale parameter (β > 0)
Lognormal (2P)	$f(x) = \frac{\exp\left[\frac{-1}{2}\left(\frac{In(x-¥)}{\sim}\right)^2\right]}{(x)\sim\sqrt{2®}}$	$¥ < x < +\infty$	σ = scale parameter (σ > 0) μ = shape parameter (μ > 0) γ = location parameter (γ = 0) *becomes the two parameter Lognormal distribution*

Weibull (2P)	$P(x)=\frac{\sim}{}\left(\frac{x}{}\right)^{\sim-1}\exp\left[-\left(\frac{x}{}\right)^{\sim}\right]$ ¥ $\leq x<+\infty$	α = shape parameter (α > 0) β = scale parameter (β > 0) γ = location parameter (γ = 0) *becomes the two parameter weibull distribution*

Source: Authors (2016)

Table 2. Potential rainfall indexes to capture maize yield-drought losses

Critical weather index at phenological phase	Description of index
Cumulative annual rainfall	Total 12-month cumulative annual rainfall
1st Wet season cumulative rainfall (April – June)	First 3-month cumulative rainfall (April-June)
Full wet season cumulative rainfall (April – Oct)	Full 8-month cumulative rainfall (April-Oct)
10-day cumulative rainfall from April 11 to 20	10-day cumulative rainfall during phenological phase (development)
10-day cumulative rainfall from April 21 to 30	10-day cumulative rainfall during phenological phase (development)
10-day cumulative rainfall from May 1 to 10	10-day cumulative rainfall during phenological phase (development)
Cumulative rainfall total < 440 mm from April 14 to May 13	Cumulative rainfall that below pre-set 420mm threshold during (development)
10-day cumulative rainfall from May 11 to 20	10-day cumulative rainfall during phonological phase (tarselling)
Minimum raindays not < 4 within 1st dekad (May 18-27)	Number of raindays must not be less than 4 times during the first 10 days (cob formation + grain filling)
10-day cumulative rainfall from May 21 to 31	10-day cumulative rainfall during phonological phase (cob formation + grain filling)
10-day cumulative rainfall from June 1 to 10	10-day cumulative rainfall during phonological phase (cob formation + grain filling)
Cumulative rainfall total < 125mm from May 18 to June 8	Cumulative rainfall that below pre-set 125mm threshold during (cob formation + grain filling)
Consecutive dry spells (deficit rainfall) from May 21-June 10	Number of consecutive of *dry days* (CDDs*)*, during (cob formation + grain filling), *(a dry day is with total rainfall < daily 2.5 mm threshold)*
Total Rainfall deficit in Development Phase	The sum of the water deficits recorded during the 10-day periods in each phase. Total deficit for "Development" is the sum of the deficits during three 10-day periods in April and May.
Total Rainfall deficit in Flowering/Reproductive Phase	
Total Deficits	Sum of "Development" and "Flowering/Reproductive" Phase deficits

Source: Authors (2016)

2.3 Minimizing basis risk

2.3.1 Detecting time trend in crop yield

Linear and quadratic regression functions were fitted using Maximum Likelihood Estimate (MLE) method to estimate time trend of the 30-year cumulative rainfall to observe any trend pattern. The gradient of the equations described the trend whether positive or negative. The regression functions estimated for the rainfall data are given by the expressions:

Linear equation: $y \sim\sim + \quad X_i + \in_i$ ……………. (2)

Quadratic regression: $y \sim\sim + \quad X_i + ¥ X_i^2 + \in_i$ ……………..(3)

where, Y_i = Annual cumulative rainfall (mm); X_i = Year (year) for time, *I;* ~ = intercept *(Y value when X=0)*; *β* = the gradient of the regression line*;* $£_i$ = stochastic error term, i =1984,1985,1986,........,2010

The null hypothesis was tested that the gradient of the regression line is zero, that is, there is no trend in the cumulative rainfall data. The coefficient of R-square (R^2) was used to explain the strength of the correlation between the variables *X* and *Y*.

2.3.2 Constructing multiple phase weather indexes

To minimize basis risk of payouts for not adequately reflecting a strong correlation with yield losses, rainfall indexes were developed in multiple phases (Giné *et al*., 2010). The growing season was divided into sequential phases of crop-growth stages as defined by maize crop phenology and cropping calendars. Maize growth stages are divided Sowing and Emergence (*Establishment*), Vegetative Growth (*Crop Development*), Flowering and Reproductive (*Tasselling, Cob Formation and Grain Filling*) phases. The schedule of payments for drought risk event was taken as piecewise linear of total 10-day climatology (dekad) rainfall deficits in each of the phases. Payment is due only if the total rainfall deficits in a phase is sufficiently below maize crop water requirements in a phase.

2.4 Test of Hypothesis

Regression equations were fitted to capture the hypothesis that there is no time trend in annual cumulative rainfall hypothesis. The Kolmogorov-Smirnov, Anderson-Darling and Chi-square goodness of fit tests were used to test the null hypothesis that cumulative 3-dacadal rainfall data have no statistical pattern in a specified probability distribution. The Kolmogorov-Smirnov statistic (KS) is defined as the largest vertical difference between the theoretical and the empirical cumulative distribution function (ECDF):

$$KS = \max_{1 \le i \le n} \left(F(X_i) - \frac{i-1}{n}, \frac{i}{n} - F(X_i) \right) \qquad \text{..................} \ (4)$$

where, X_i is a random variable, *i* =1, 2,….., n, CDF = $F_n(X) = \frac{1}{n}$. [Number of observations ≤ x]

This test is used to decide if a sample comes from a hypothesized continuous distribution. Anderson-Darling statistic $\left(A^2\right)$ is expressed as:

$$A^2 = -n - \frac{1}{n}\sum_{i-1}^{n} (2i-1).\left[InF(X_i) + In\left(1 - F(X_{n-i+1})\right)\right] \quad \text{..............} \ (5)$$

It is a test to compare the fit of an observed cumulative distribution function (CDF) to an expected cumulative distribution function. This test gives more weight to the tails than the Kolmogorov-Smirnov test. Chi-square is a statistical test commonly used to compare observed data with data we would expect to obtain according to a specific hypothesis. The chi-square test is always testing what researchers referred to as the null hypothesis, which states that there is no significant difference between the expected and observed result.

The Chi-Squared statistic is defined as:

$$X^2 = \sum_{i-1}^{k} \left(\frac{(O_i - e_i)^2}{e_i} \right) \quad \text{...............}(6)$$

Where O_i = observed frequency, e_i = expected frequency, *'i'* = number of observations (1, 2, …….k), estimated by: $e_i = F(X_2) - F(X_1)$, F = the CDF of the probability distribution that was tested. The observed number of observation (k) in interval *'i'* was computed from equation given as:

$$k = 1 + \log_2 n \qquad \text{…………… (7)}$$

n = sample size

These goodness of fit tests were fitted to the annual rainfall of 30 year period, 1st wet season, and the 2nd wet season rainfall data. These tests were performed to measure the compatibility of the random cumulative 3-dacadal rainfall data with eight theoretical probability distributions. The test statistic of each test was computed and tested at α =0.01 level of significance. The Durbin-Watson test states that: Ho: $\rho = 0$ and $H_1 : \rho > 0$. The test statistic states that:

$$d = \frac{\sum_{i=2}^{n} (e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \qquad \text{………………………..(8)}$$

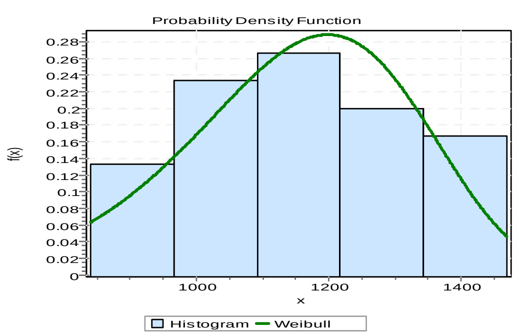
where, $e_i = y_i - \hat{y}_i$ and y_i and $\hat{y}_i$ are, respectively, the observed and predicted values of the response variable for individual *i*. d becomes smaller as the serial correlations increase. Upper and lower critical values, *dU* and *dL* have been tabulated for different values of k (the number of explanatory variables) and n. ***Decision rules:*** If d < dL reject H_o: $\rho = 0$; If d > dU do not reject H_o: $\rho = 0$; If dL < d < dU test is inconclusive.

Results and discussions

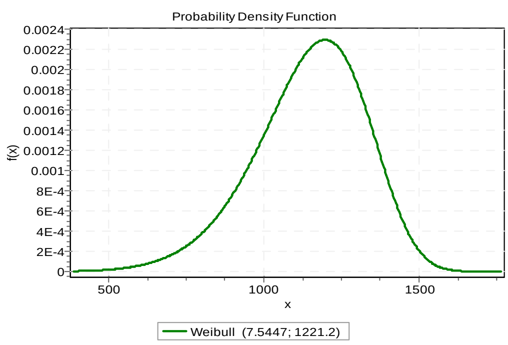
1 Predicting drought risk from probabilistic forecasting

Given that rainfall is the most critical element that determines rain-fed agriculture, quantifying seasonal rainfall variability is a first step of developing adaptation interventions. Figure 3 presents fitted Weibull probability density function for the 3-decadal rainfall data for Central-West Nigeria. It is observed that the distribution fitting on the histogram bar modeled a Weibull distribution. The Weibull function has a skewness value of -0.50 which serves as a pointer that distribution of the 3-decadal rainfall is negatively skewed (not symmetric), since the left tail of the distribution longer than the right tail. This is a further indication that most of the rainfall values are concentrated on the right of the mean with extreme values to the left, hence Central-West Nigeria is experiencing significant very low rainfall than normal over the past 3 decades. It is evident that the region is exposed to drought risk with implication for food crop production arising from deficit-rainfall.

Figure 3. Fitted weibull distributions for the 3-decadal rainfall



(a)

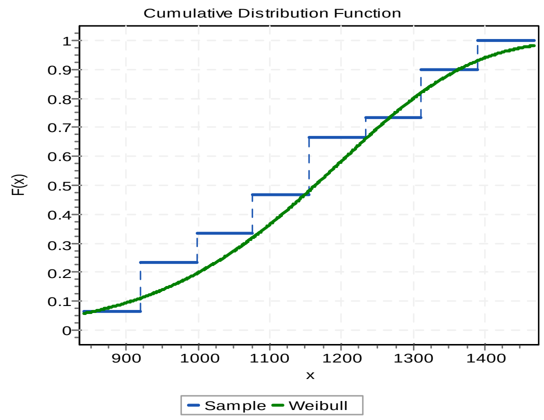


(b)

Source: Field data (2016)

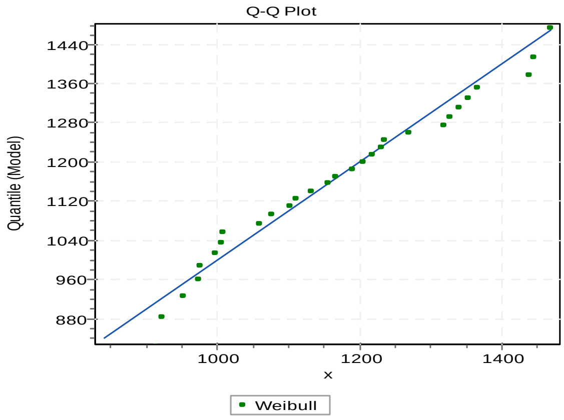
The Cumulative Distribution Function (CDF) is presented in Figure 4 indicating that the Weibull probability distribution was well fitted to the 30-year rainfall data in the study area.

Fig 4. Weibull cumulative distribution of decadal rainfall rainfall



Source: Field data (2016)

Fig 5. Weibull quantile-quantile plot for decadal



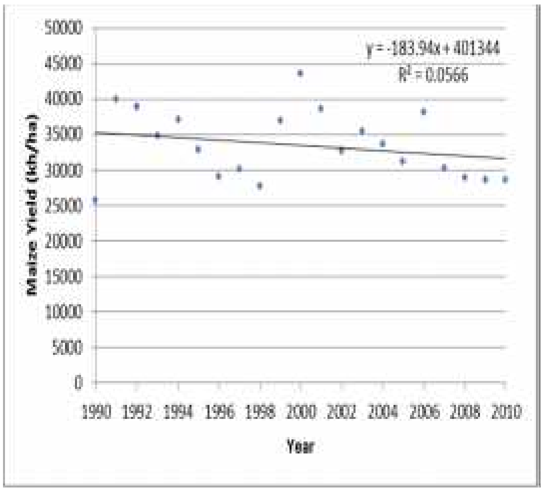
Source: Field data (2016)

The Quantile-Quantile plot presented on Figure 5 provided a useful diagnostic of how well the specified theoretical Weibull distribution fits the quantiles of the 30-year daily rainfall for the study area. The reference line corresponds to the estimated values for the threshold and scale parameters of α =7.5447, β =1221.2. The Normal Q-Q plot indicates that the Weibull distribution well corresponds, hence the correct model for the 30-year rainfall data.

2 Time trend analysis of maize yield (wet season) and rainfall

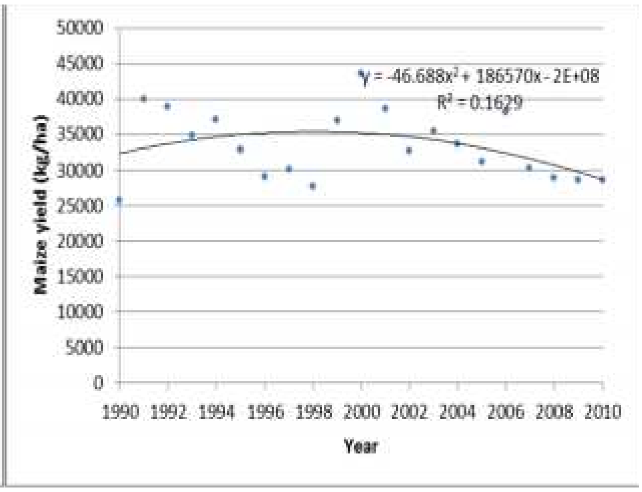
Linear and quadratic regression functions were fitted to capture time trend that maize yield per unit land is constantly increasing due to technological improvements. Figure 6 presents that yield losses/ha were observed in maize production in 1996, 2002, sharply declining after 2008 in both regression models. Yield losses are expected at every 6-year interval.

Fig.6. Maize yield linear regression with time trend time trend



Source: Field data (2016)

Fig. 7. Quadratic regression of maize yield with



Source: Field data (2016)

When expand the observed data range**,** a non-linear function seems a much more realistic approximation of the yield-time relationship as indicated in Figure 7, quadratic function has a better R^2 of 21.1% than linear function, estimate of intercept of linear time trend suggests no significant time trend in yield variations, hence was used to predict yield losses to rainfall indexes in this study.

3 Calibrating optimal deficit-rainfall indexes

The statistical relationships were obtained for maize *development stage* between April 14 and May 13 and the *reproductive phase (cob formation + grain filling)* between May 18 and June 8 adequately explained the causal-effect relationship between historical maize yield data and the selected rainfall indexes based on deficit rainfall risk periods for maize in the study area. The correlation results between maize yields and weather indexes are shown in Table 4.

Table 4. Regression statistics and correlations of rainfall indexes and maize yield

Rainfall Index	**Regression Equation**	**Correlation Coefficient, r**	**R^2**	**D-Watson Statistic**
Cumulative annual rainfall	$y = 31042.73 + 2.06X$	0.07	0.005	1.195
Full wet season cumulative rainfall (April – October)	$y = 29304.30 + 3.806X$	0.13	0.017	1.183
10-day cumulative rainfall deficit April 11-20	$y = 35001.39 – 33.77X$	0.18	0.031	1.428
10-day cumulative rainfall deficit April 21- 30	$y = 36492.16 – 63.01X$	**0.33**	0.106	1.297
10-day cumulative rainfall deficit May 1-10	$y = 37227.57 – 28.22X$	**0.27**	0.072	1.363
Cumulative rainfall total < 440 mm from April 14 to May 13	$y = 31765.72 + 37.31X$	0.32	0.105	0.911
Minimum raindays not < 4 within 1st dekad (May 18-27)	$y = 32028.32 + 28.61X$	0.20	0.039	1.189
10-day cumulative rainfall deficit May 21- 31	$y = 33014.37 + 7.40X$	0.05	0.003	1.277
10-day cumulative rainfall deficit June 1- 10	$y = 28709.77 + 39.64X$	0.32	0.104	1.249
Cumulative rainfall total < 125mm from May 18 to June 8	$y = 36666.90 –221.31X$	0.12	0.014	1.225
Consecutive dry spells (deficit rains) from May 21-June 10	$y = 24952.71 – 28.22X$	**0.27**	0.072	1.363
Total deficit in development phase	$y = 24952.71 – 28.22X$	0.27	0.072	1.363
Total deficit in flowering/reproductive	$y = 37297.82 + 23.79X$	0.24	0.058	1.071
Total Rainfall Deficits	$y = 33215.68 – 0.558X$	0.01	0.000	1.268

Source: Field data (2016)

There is an overall weak statistical relationship between maize yield and all the rainfall indexes constructed. It is evident that stronger rainfall indexes would be very difficult to be established for the region given the inability of yield data to be disaggregated at district-level. However, based on the most critical rainfall risk period, highest correlation coefficients were obtained for a possible prototype rainfall index insurance design.

Table 5 presents the correlation analysis of two strongest correlated rainfall indexes in the *development phase* namely the *2nd dekad cumulative rainfall climatology* and *3rd dekad cumulative rainfall climatology.* The 2nd dekad cumulative rainfall climatology during maize vegetative growth period is positively correlated with yield (r=0.33) per unit of cultivated land while 3rd dekad cumulative rainfall climatology during maize vegetative growth period is also positively correlated with yield (r=0.27) per unit of cultivated land. This suggests that based on the crop water requirement of maize, water is scarce during both the second and third dekads of development and reproduction stages in study area. These two rainfall indexes are critical for maize phenological growth, hence affecting crop yield levels. However, the indexes fairly predict maize yield losses in the study area.

Table 5. Correlation of weather indexes and maize yield (development stage)

Maize Growth Stage	**Development Phase**	
	2nd dekad cumulative rainfall	***3rd dekad cumulative rainfall***
Start and end date	April 21-30	May 1-10
Correlation	0.33	0.27
Durbin -Watson statistic	1.297	1.363

Source. Computed from data analysis, 2015

The Durbin-Watson (D-W) statistic was used to test for autocorrelation in the residuals from the statistical regression analysis performed between the 20-year time series maize yield and rainfall indexes that well predict yield losses. The DW (1.297) < dL of 1.5 obtained for the 2nd dekad cumulative rainfall and DW (1.363) < dL recorded for the 3rd dekad cumulative rainfall indicate positive autocorrelation at 5% level of significance. Therefore, we reject Ho and accept Ha that there is positive serial correlation of the residual errors between rainfall indexes and maize yield.

The correlation analysis on Table 6 presents two strongest correlated rainfall indexes in the *reproductive stage (cob formation + grain filling)* namely the *Consecutive dry spells (deficit rains) from May 21-June 10.* During maize reproductive stage, this index is positively correlated with yield (r=0.27) which suggests rainfall deficits for maize cob formation and grain filling given the crop water requirement of maize in the study area. This index is critical for maize cob formation and grain filling, hence affecting crop yield levels. The index also fairly predicts maize yield losses in the study area.

Table 6. Correlation of weather indexes and maize yield (Reproductive stage)

Maize Growth Stage	**Reproductive Phase**
	Consecutive dry spells (deficit rains) from May 21-June 10
Start and end date	June 1-10
Correlation	0.27
Durbin -Watson statistic	1.249

Source. Computed from data analysis, 2015

The hypothesis was tested that residual errors between rainfall indexes and maize yield are independents. The DW (1.249) < dL of 1.5 obtained for the 3rd dekad cumulative rainfall climatology and *DW* (1.363) < *dL* recorded for the consecutive dry days of total rainfall < daily 2.5 mm threshold show that errors are positively autocorrelated at 5% level of significance. We therefore reject H_o and accept H_a that residual errors of rainfall indexes and maize yield exhibit positive serial correlation. The tested H_o that there is no positive serial correlation in the residual errors of yield and indexes is rejected while the alternate hypothesis that there is no positive serial correlation in the residual errors of yield and indexes is therefore accepted at 5% level of significance. Therefore attempt to design possible rainfall insurance contract as adaptation instrument against yield losses from drought risk event is fairly reasonable.

Summary and conclusion

The study found that quadratic function was found more realistic approximation of the yield-time relationship than linear function, estimate of intercept of linear time trend suggests no significant time trend in yield variations, hence better able to predict yield losses to rainfall indexes. Hence, there is an overall weak statistical relationship between maize yield and all the rainfall indexes constructed in middle belt of Nigeria. It is evident that based on the most critical rainfall risk period, highest correlation coefficients were obtained for a possible prototype parametric rainfall insurance design.

The two strongest correlated rainfall indexes in the *development phase* of maize crop are the *2nd dekad cumulative rainfall climatology* and *cumulative rainfall below pre-set 440mm threshold.* The 2nd dekad cumulative rainfall climatology during maize vegetative growth period is positively correlated with yield (0.33) per unit of cultivated land which suggests that water is scarce during the second dekad of growth and development stage. The cumulative rainfall below a pre-set 440mm threshold during maize vegetative growth period is positively correlated with yield (0.32) per unit of land cultivated. These two rainfall indexes are critical for maize phenological growth, hence affecting crop yield levels.

The two strongest correlated rainfall indexes in the *reproductive stage (cob formation + grain filling)* are the *3rd dekad cumulative rainfall climatology* and *consecutive dry days of total rainfall < daily 2.5 mm threshold.* The 3rd dekad cumulative rainfall climatology during maize reproductive stage is positively correlated with yield (0.32) which suggests rainfall deficits for maize cob formation and grain filling. The consecutive dry days < daily 2.5 mm threshold during maize reproductive stage is positively correlated with yield (0.27). These 4 indexes are critical for maize cob formation and grain filling, hence affecting crop yield levels. The indexes weakly predicted maize losses in the savannah agro-ecological zone of Nigeria.

Policy implications for enhancing farmers risk management

This paper therefore concludes that the rainfall pattern and distributions in the savannah region of Nigeria fairly predict maize crop yield, hence do not fully capture maize crop losses. It should not be completely rely on to serve as prozy for measuring income losses in the agro-ecological zone. Rainfall-index insurance possibly can be a promising risk-transfer instrument but only shows weak signals of its capability of providing index-based insurance protection against farmers' losses. Serious caution should be exercised at the initial stage of rainfall-index construction for designing maize insurance contract given that the success of any weather insurance product heavily lies on a very strong correlation between crop yield and weather indexes constructed. Other safety nets should be added to complement this risk sharing management tool in Central-West Nigeria.

Acknowledgements

I acknowledge the generous research scholarship and funding of this study by the German Ministry of Education and Research (BMBF), Germany, for my candidature in the Graduate Research Programme of Climate Change Economics, Department of Economics, Université Cheikh Anta Diop, Dakar, Senegal under the initiative of the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) Accra, Ghana. I would also like to thank Dr. Williams M. Fonta and Dr. Safiétou Sanfo at the WASCAL Competence Center for their painstaking contributions to the review.

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This paper was presented at the Conference on Climate Change and Food Security in West Africa co-organized by Université Cheikh Anta Diop de Dakar (UCAD) and Center for Development Research (ZEF), University of Bonn, on 17-18 November 2019 in Dakar, Senegal.