Drought Triggered Index Insurance Using Cluster Analysis of Rainfall Affected by Climate Change

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Abstract

Farming usually tops the list among the agricultural practices that generate income for large percentage of the population in developing countries including Ghana. Agricultural farming represents 36 percent of Ghana's GDP and is the main source of income for majority of the population. Similar to other developing countries, weather pattern changes in Ghana have negatively impacted their agrarian practices and crop production. One of the weather factors that have major potential for impacting crop growth and therefore crop yield is the amount and timing of rainfall received during the growing season. One way, in which farmers can recover from these crop losses, is having coverage through agricultural insurance. However, traditional insurance has several drawbacks including high administrative costs and moral hazard. An alternative to traditional insurance is index based insurance. Index based insurance is an agricultural insurance scheme that pays for losses based on an index. Index insurance contracts, such as rainfall insurance, attempt to circumvent the moral hazard and adverse selection issues that are prevalent in traditional insurance. Accordingly, developing weather based crop insurance associative model, such as, rainfall with crop yield may provide satisfactory result. This requires constructing a threshold that identifies trigger in the rainfall for signaling drought to indicate crop loss. Thus, the occurrence of a trigger that signals payment for crop loss is therefore a very important component in the pricing of index insurance. We introduce model-based clustering as an approach for determining an optimal trigger in rainfall for drought identification. Many researchers create an arbitrary threshold of rainfall amount (e.g., rainfall below 10 percent of normal yield level) to identify drought however this method of identification may not be suitable because of the subjective nature. To avoid subjectivity, we have applied cluster analysis, an objective approach, to separate rainfall into groups with similarity in characteristics based on crop yield in constructing a drought trigger.

[Key words: drought trigger, crop index insurance, climate change.]

INTRODUCTION

Agricultural is an important source of income for the large group of population in developing countries. Farming usually tops the list among the agricultural practices that generate income for large percentage of the population. In Ghana, farming represents 36 percent of the country's GDP and is the main source of income for 60 percent of the population. In recent years, along with other developing countries, weather variations in Ghana have negatively impacted their agricultural economy (Etwire et al., 2013). Loss of agricultural income including destruction of crops and livestock drive poor farmers into complete poverty and leave them with very little chance for reclaiming their livelihood. Indirect impacts from loss of income include sub-optimal management of financial risk exposures, for example, selecting low-risk, low-return asset and activity portfolios that reduce the risk of greater suffering, but limit growth potential and investment incentives, selling assets (at inopportune times). The problem gets more exacerbated by the reaction of financial institutions, which may restrict lending to farmers to minimize exposure to agricultural risk. In addition, insurers may avoid underwriting policies that have positively correlated risks (Schoder, Zweifel, and Eugster, 2013). All of these indirect consequences combined can hinder overall economic growth of the country (Barnett et al., 2008).

Weather conditions may impact crop growth on varying level and therefore, influence crop yield. However, the effect of weather on crop yield also depends on other agronomic factors such as, fertilizer use, plant density, soil type, and soil condition. One of the major weather factor having impact on crop yield is the amount of rainfall received during growing season (availability of water for regions without access to irrigation). In many parts of the world, the rainfall amount affects water availability in the soil, crop type, growth patterns of crops, and yield outcome of crops (Al-Kaisi & Broner, 2011). However, the amount of rainfall may also be associated with sea surface temperature (SST). El Niño is one of the anomalies that influence SST variations. El Niño is a naturally occurring phenomenon that fluctuate the sea surface temperature (SSTs) and the wind pattern across the equatorial Pacific Ocean. During an El Niño episode, the usual rise of sea surface temperature of the tropical Pacific Ocean is between 0.5 °C to 0.9 °C. In general, El Niño impacts weather through changes in seasonal rainfall amount which can affect agriculture production. The relationship between water availability and yield outcome is dependent upon the particular crop's sensitivity to water deficiency during planting and growth stages. In general, crops are more sensitive to water deficiency during emergence, flowering, and early fruit formation stages. Consequently, lack of rainfall or excessive rainfall at the wrong time of growing season can cause heavy crop losses. One way, in which farmers can deal with these losses is through agricultural insurance. It is one of the most useful tools for managing the financial risks associated with farming. However, traditional insurance has several drawbacks, specifically in developing countries because of its high transaction costs, involves significant government subsidization, and has other challenges that may hinder the protection from risk (Skees, 2008). In order for an insurance scheme to work, the purchasers must perceive that the premiums and expected benefits offer value; while the sellers must see opportunity for a positive actuarial (statistically reliable) profitable outcome over time. An example of a traditional agricultural insurance product is a "yield protection" (YP) and it covers unavoidable production losses caused by drought, excessive moisture, plant disease, higher than usual temperature during pollination, wildlife damage, fire and other weather related causes. YP provides yield guarantee, based on regional average yield or on individual historic yield, where the main risks affecting yield (e.g. drought) are comprised. This type of traditional crop insurance relies on direct measurement of the loss or damage suffered by the farmer. However, field loss assessment is usually costly and may not be feasible, particularly where there are large numbers of small-scale farmers. This creates a challenge in the implementation process.

An alternative to traditional insurance is index based insurance instruments. Index based insurance is an agricultural insurance scheme that pays for losses based on an index, an independent and objective measure that is (presumed to be) highly correlated, with crop yield. Index insurance contracts, such as rainfall based insurance, attempt to circumvent the moral hazard and insurance fraud issues that are prevalent in traditional insurance (Skees, 2008). Lesch and Baker (2013) using a consumer survey identified factors contributing to the insurance fraud environment. The International Fund for Agricultural Development (IFAD) has been working for many years on index insurance as part of its commitment to reduce vulnerabilities of rural small-farm-holders and open their access to a range of financial services with the sole aim of improving their livelihoods (IFAD and WFP, 2010). In this regard, index insurance that is weather based may be more appropriate for northern Ghana due to overall absence of irrigation system. Water stress has substantial potential for impacting crop production (see, Bannayan et al., 2008) and therefore crop yield. This is specifically noteworthy in regions where irrigation systems are nonexistent. Thus, developing weather based crop insurance, such as; drought trigger (Chantarat et al., 2007) for crop loss may provide alternative protection for small-farm holders in Ghana.

The primary objective of crop insurance is to provide protection against yield shortfalls due to the effect of external factors. External factors include weather factors that results in drought, flood, and hail can impact the crop yield and may create variations in crop productions. Thus, an associative modeling process to understand the crop yield pattern that accounts for yield variations (change) over time is an objective for index formation. Researchers have explored various procedures, such as linear trend, quadratic trend, polynomial trend (see, Just and Weninger**,** 1999; Cooper, 2010) in order to de-trend the yield over time and isolate the real effect. Several studies have identified critical thresholds (Prasad et al., 2006) that occur due to external influences. Critical thresholds occur when the outcome of a process over time is not a single linear (or nonlinear) function of time, but changes abruptly at some threshold point. Changes in management regimes may have threshold type effects on the response processes. For example, change in fertilizer application due to environmental regulation, or government subsidy may cause a threshold in the long-term crop yield dynamics. In addition, other non-linear methods, such as, piecewise regression have been applied and found to be useful for understanding crop yield patterns (see, Skees et al., 1997; Choudhury et al., 2015).

Index-based insurance

Index-based insurance is an agricultural insurance scheme that pays for losses based on an index, an independent and objective measure that is highly correlated with losses. Weather indexed insurance payment occurs based on realizations of weather index that is highly correlated with an outcome variable such as crop yield. Index-based insurance contracts circumvent the moral hazard and adverse selection issues. Farmers in developing countries are vulnerable to a range of risks and constraints that impede their socio-economic development. Weather shocks can trap farmers and households in poverty, but the risk of shocks also limits the willingness of farmers to invest in measures that might increase their outcome and improve their economic environment.

Research studies of crop insurance have shown that the popularity of index-based insurance can be attributed to the failures, and high costs, of traditional insurance. Glauber (2004) discussed the performance of crop insurance in U.S.A and the measures taken to rescue the crop insurance program. Much of the interest in favor of area-based yield insurance has been motivated due to the concerns and limitations with the traditional individual farm-loss crop insurance (Skees, 1994; Halcrow 1949; Miranda, 1991).

In comparison with traditional agricultural insurance, index-based insurance lowers the threshold of insurability, i.e. the economic size of an insurance transaction that can be reasonably serviced by an insurer. The simplified nature of the product offers additional opportunities to reach a wider range of market segments and an innovative design to target the small-scale farmers. However, the other potential target groups may be aggregate villagers and commercial farmers.

Index-based insurance works best where it takes an integrated approach to risk management, that additionally includes access to finance and capital, improved seed, and product markets. In developing countries, index-based insurance can be considered for two broad purposes:

a. Index-based insurance can be used as a tool to promote agricultural and rural development. It can help households, financial service providers and input suppliers; and manage low-to-medium-frequency covariate risks such as drought.

b. Index-based insurance can provide an alternative method of funding for disaster recovery assistance programs and may be a requirement for loan approval process by financial institutions.

Weather and Climate change effect

Atmospheric occurrences that have a daily presence are connected to the disciplines of 'weather' and 'climate'. The atmospheric fluctuations occurring from hour to hour and day to day make up the *weather*. Characteristics such as temperature, air pressure, humidity, cloudiness, precipitation and wind are all daily components of weather. *Climate* is usually defined by how atmosphere behaves in both the average conditions and in anomalous weather conditions for some particular geographic region over long periods of time.

Both weather and climate have shown to affect crop growth and crop yield. Availability of water is an essential for optimal crop growth because crops consume substantial amount of water and release it through evapotranspiration during the growth period. The difference between the evapotranspiration requirement for optimal growth of crops and the water availability to crops is the water deficit that has the potential to reduce the crop production. If rainfall amount is insufficient for specific growth period and persists during the growing season, the crop production will very likely suffer. If this phenomenon occurs repeatedly and over prolonged periods of time, it is a likely indication of certain changes in climate.

Agriculture practices are highly dependent on specific timing of various climatic conditions for crop growth and consequently crop yield. In general, increases in atmospheric temperatures and precipitation up to a certain level can be beneficial for crop production. However, climate changes such as, increase in the frequency and severity of droughts or floods could pose severe threats to farming. Therefore, climate change can make it more challenging for crop production (Carriquiry and Osgood, 2012). The effect of climate change also needs to be considered along with other factors that affect agricultural production, such as farming environment, farming practices, and application of technology. Therefore, trying to understand the effect of climate change on our food supply is a worthy endeavor. However given the multi layered nature that makes up the elements of climate change, identifying the effect of climate change on our food supply can be very complex and daunting task. Many main stream scientific models of crop production dealing with climate change mainly consider factors such as temperature, precipitation, and carbon dioxide. However, many other processes not easily incorporated into these models that could potentially have significant effects on crop productivity including increase in inter-annual climate variability associated with phenomena like El Niño. Atmospheric phenomena like El Niño have shown to impact temperature and/or precipitation that increase frequency and intensity of extreme weather and usually persist for several years (Moy et al., 2002; Trenberth, 1997). Consequently, this phenomenon has greater potential to manifest climate change and have significant impact on crop yield. As a result, it is noteworthy to capture the degree of real association between crop yield and precipitation as related to all aspects of climate change.

In our analysis, we have found evidence that crop yield is significantly affected by climate change and therefore, has the potential for use as a significant indicator of changes in crop production over time. This signifies the observation of the intensity of indirect environmental effect on our food source (Nieto et al, 2010; Skees, 2000). Also, the result obtained suggests the existence of clusters of rainfall based upon crop yield that can be used for drought trigger. Finally, this research provides evidence of statistically significant association between crop yield and rainfall, and suggests for implementing feasible rainfall-based index insurance.

DATA AND RESEARCH METHODOLOGY

Crops that are likely to be suitable for weather based index insurance include rain-fed maize and rice. Associative models relating crop yield with explanatory variables, such as rainfall can be used to estimate crop production. In addition, univariate time series forecasting methods can also be applied for crop yield prediction (Choudhury and Jones, 2014). Associative model's performance generally improves after trends are eliminated from the crop yield. Therefore, one of the objectives is to identify a statistical technique that may effectively eliminate or at least reduce the trend effect from the crop yield. By applying trend elimination technique, an absolute relationship between crop yield and weather factor "rainfall" can be observed explicitly. Adequate formulation of the response function is very important for understanding the crop yield pattern and identification of external association. Crop yield data that are collected from the field are usually very noisy and the relationship between weather factors and yield responses are in general unclear due to amalgamated variations. To reduce these variations, we have used three-period moving average MA (3) smoothing technique, so the yield pattern and its trend are easily discernible. Moreover, it is necessary to take into account the diminishing effects of water need and the increasing nature of the yield response function. We assume that the higher the rainfall amount, the higher the yield, until at certain point beyond which the added rainfall attain a saturation level and does not improve the yield any further. Therefore, it is advisable to formulate the response function as a quadratic equation of rainfall.

For this study, we have collected data from The Ministry of Food & Agriculture, the main government organization responsible for implementing agricultural policy in Ghana. Their statistical service department is an independent government department that is responsible for the collection, compilation, analysis, publication and dissemination of official statistics in Ghana for general and administrative purposes. In this paper, crop yield (metric tons of crop production per hectare) refers to the ratio of total production in a district (region) divided by total land cultivated in that district. The areas (regions) are administrative units called districts, as this is the scale at which most socioeconomic data and crop statistics are available. Rainfall data were collected from the rainfall station of that district and are reported in millimeters (mm).

Weather conditions can be a source of uncertainty when considering crop yield production in large areas. A robust array of research have been conducted to identify effects of weather factors and the uncertainty it triggers on crop yield by researchers modeling crop yield and researchers modeling climate and weather (Russel & Gardingen, 1997). Crop yield models concentrates on soil condition (Pachepsky & Acock, 1998) and weather factors that affect crop yield to ascertain the uncertainties in yield management. Whereas, the climate model researchers focus on identifying the weather conditions that affect crop production and quantifies the crop yield outcome related to climate change (Hoogenboom, 2000; Mearns et al., 2001; Semenov and Porter, 1995). Many of the research related to weather factors and crop yield have suggested that when assessing a large area (such as a province or district), weather factors are more related to crop yield uncertainties than soil variations (Etwire et al., 2013; Hansen et al., 2006; Jones et al., 2000). The Northern region of Ghana is considered to be the major bread basket of the country and therefore our research is concentrated on the data from that region. This region is also the most susceptible to weather variation specifically to the lack of rainfall. All agricultural practices including farming in this region are practically 100 percent dependent on rainfall (Stutley, 2010). Our study will explore to create drought trigger using cluster analysis of rainfall under the assumption of correlated yield and rainfall for index insurance.

Cluster analysis for identifying drought trigger

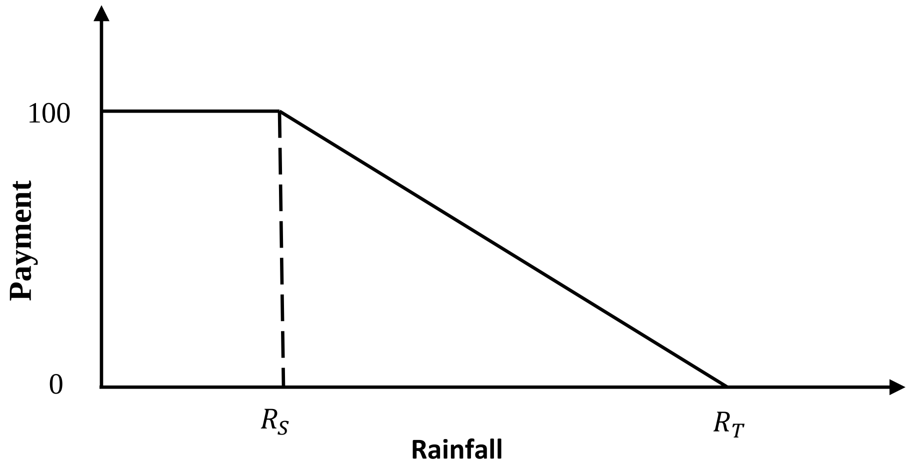
The trigger that signals for payment due to crop loss is very important in the pricing of index insurance products and therefore it is desirable to obtain an optimal trigger for indication of crop loss. We introduce the model based clustering as an approach for determining an optimal trigger in rainfall for drought identification. Drought may be defined and characterized in many ways (Skees, 2001). However, drought in general is an effect of rainfall (water) deficiency and thus results in crop loss due to negative impact on crop production. Many researchers create an arbitrary threshold of rainfall amount (e.g., rainfall below 10 percent of normal yield level) to identify drought that is subjective and may not be appropriate. Therefore, we have applied cluster analysis approach to separate rainfall into groups with similarity in characteristics based on crop yield. We are interested in creating clusters of rainfall such that higher rainfall is grouped together with higher crop yield and lower rainfall is grouped together with lower crop yield. Cluster analysis classifies observations (or objects) so that each object is very similar to each other within the cluster with respect to some criterion (or factors). The resulting clusters of observations should then exhibit high internal homogeneity and high external heterogeneity. Therefore, cluster analysis is a data analysis tool for organizing observed data (e.g. people, objects, events, countries) into meaningful groups, or clusters, based on combinations of relevant factors, which maximizes the similarity of observations within each cluster while maximizing the dissimilarity between clusters. Cluster analysis creates new groupings without any preconceived notion of cluster formation, whereas discriminant analysis classifies observations and items into already known categories. Each cluster thus describes, in terms of the data collected, the class to which its members belong. Items in each cluster are similar in some ways to each other and dissimilar to those in other clusters. Thus, if the classification is successful, the observations within cluster will be close together and different clusters will be far apart when plotted in a graph. Cluster analysis, similar to factor analysis, makes no distinction between dependent and independent variables (or factors). The entire set of observations is used for interdependent relationship in cluster analysis. Factor analysis reduces the number of variables by grouping them into a smaller set of factors. On the other hand, cluster analysis reduces the number of observations (or measurements) by grouping them into few clusters. We have applied model-based clustering process (Fraley & Raftery, 2007) in our analysis. The “mclust” package of “R” software is used to perform the cluster analysis on our rainfall data and the resulting clusters appear to fit our data well.

Association of weather and crop yield

The basis for designing weather-based index insurance aimed at agricultural crops is the existence of significant associations between the outcome variable of interest in our case crop yield and weather factor, such as rainfall. The weather based insurance instrument is developed in such a way that when rainfall exceeds a predetermined threshold, at which payment is triggered, and the payment structure can be proportionate to index beyond the threshold or a specific quantity of the insured amount. Pricing of the index-based insurance product is based on the underlying payment structure and the probability of realizations of the index that might exceed the threshold to trigger payment. While index-based insurance products have advantages in reducing adverse selection and moral hazard, insurers are subject to some basis risk (Doherty and Richter, 2002). One of the key challenges in developing an index-based insurance that minimizes the basis risk is to identify a proper index factor (Chantarat et al., 2013). For index-based insurance, basis risk reflects the difference between the realized index’s expected loss and the actual crop loss. Since the individual farm yields are not perfectly correlated with the insured index, insurers of index-based insurance are exposed to the basis risk. For example, it is possible for the insurer of a temperature-based (Okhrin, Odening, and Xu, 2013) or rainfall-based indexed insurance policy to experience production loss and yet not eligible to receive a payment because there has been no occurrences of trigger for temperature exceeding or rainfall shortage. Similarly, it is possible for an insurer to receive a payment when no crop losses have occurred. Therefore, an effective weather induced crop yield model is critical in constructing satisfactory weather-based index insurance. In addition, introducing the climate change information into the weather-yield association model has the potential to improve the effectiveness of weather-based index insurance. With higher correlation there will be less basis risk. In establishing this relationship it is critical to consider the need of rainfall for optimal growth at different stages of crop life cycle. In our analysis we have found planting season (March) rainfall to be consistently significantly correlated with crop yield. Once a strong association is established, drought is determined by comparing the rainfall with a predetermined threshold for crop loss.

Pricing and payment structure for drought insurance

Consider a rainfall index insurance which pays the entire Insured Amount (IA) if actual rainfall R_A for the district in March drops below the stop-loss rainfall R_S, pays the proportion $IA\left(\frac{R_T-R_A}{R_T-R_S}\right)$ when the rainfall is between the stop-loss rainfall R_S and trigger rainfall R_T , and pays nothing when the rainfall exceeds the trigger rainfall R_T as shown in the figure below.



Therefore, the payment can be expressed as,

$$Pay\ out = \begin{cases} IA & ,\ if\ R_A \le R_S \\ IA\left(\dfrac{R_T - R_A}{R_T - R_S}\right) & ,if\ R_S < R_A \ \le R_T \\ 0 & ,\quad if\ R_A > R_T \end{cases}$$

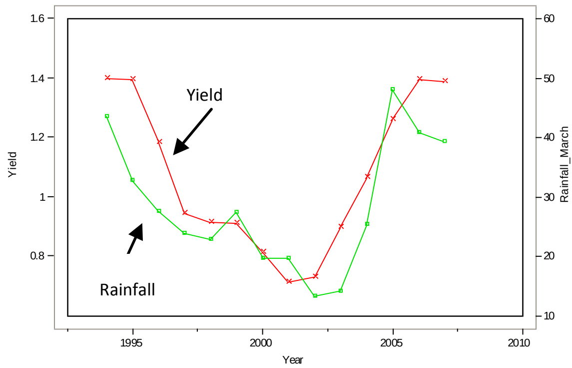
$$E(Pay\ out) = IA\int_0^{R_S} f(R_A)\, d_{R_A} + \int_{R_S}^{R_T} IA\left(\frac{R_T - R_A}{R_T - R_S}\right) f(R_A) d_{R_A}$$

$$E(Pay\ out) = IA\int_0^{R_S} f(R_A)\, d_{R_A} + \frac{IA}{R_T - R_S}\int_{R_S}^{R_T} R_T\, f(R_A) d_{R_A} - \frac{IA}{R_T - R_S}\int_{R_S}^{R_T} R_A\, f(R_A) d_{R_A}$$

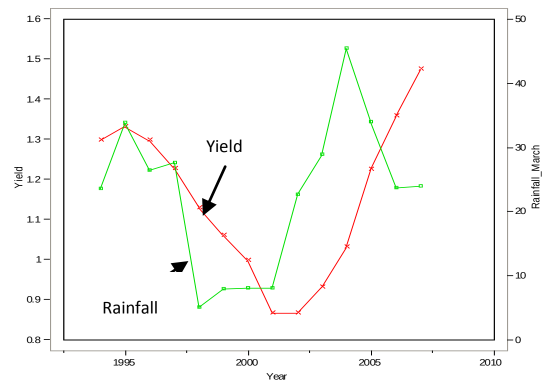
$$E(Pay\ out) = IA\big(F(R_S)\big) + \frac{IA}{R_T - R_S}\Big(R_T\big(F(R_T) - F(R_S)\big)\Big) - \frac{IA}{R_T - R_S}\int_{R_S}^{R_T} R_A\, f(R_A) d_{R_A}$$

Since, $Premium = Present\ Value\ [E(Pay\ out)]$

$$Premium = (e^{-rt})\ \left[IA\big(F(R_S)\big) + \tfrac{IA}{R_T - R_S}\Big(R_T\big(F(R_T) - F(R_S)\big)\Big) - \tfrac{IA}{R_T - R_S}\int_{R_S}^{R_T} R_A\, f(R_A) d_{R_A}\right]$$



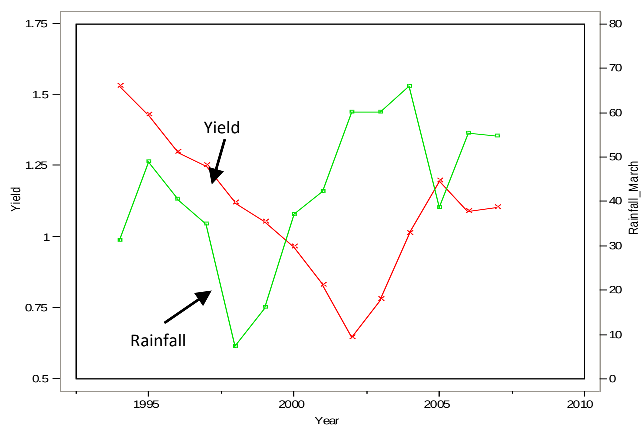
Graph1: Plot of Yield and Rainfall in Tamale



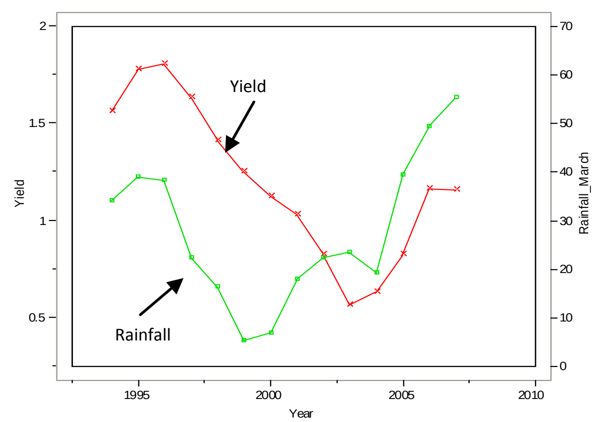
Graph2: Plot of Yield and Rainfall in Yendi

EMPIRICAL RESULTS: A case study of Ghana

Ghana produces a variety of crops in various climatic zones which range from dry savanna to wet forest. This research primarily uses data from four districts namely, Tamale, Damango, Salaga, and Yendi in the northern region of Ghana. The northern region of Ghana is considered to be the major bread basket of the country, and is also the most susceptible to the weather and climate change, especially the recurring lack of rainfall.



Graph3: Plot of Yield and Rainfall in Salaga



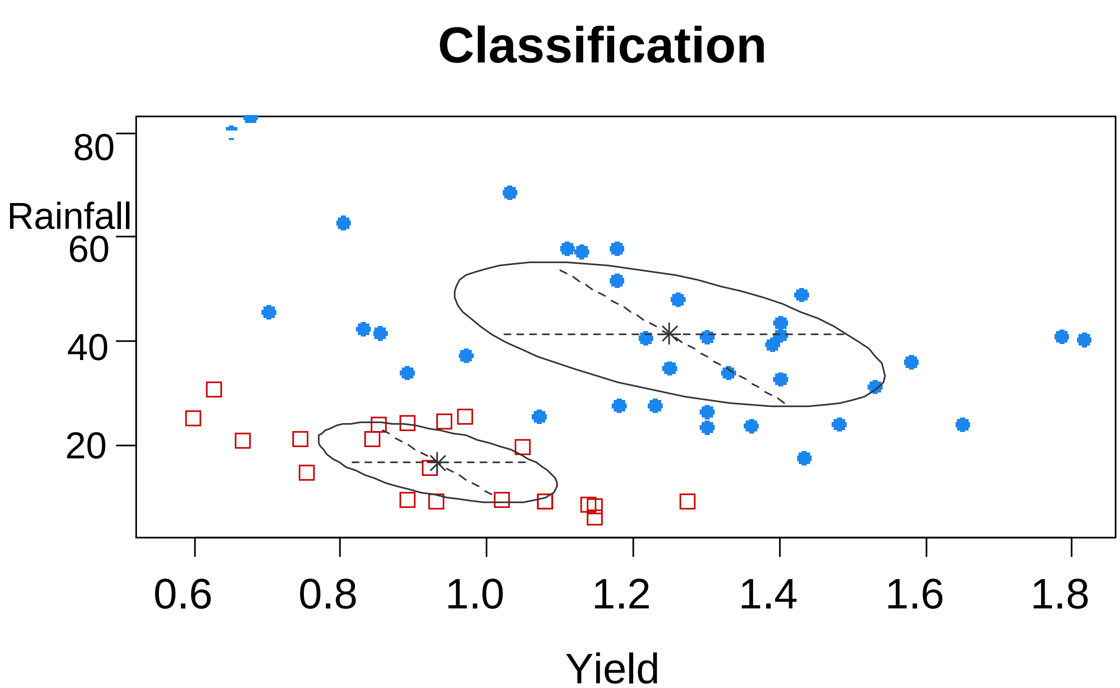
Graph4: Plot of Yield and Rainfall in Damango

The trends in yield for four different districts demonstrate that the trends are not linearly related with respect to time (see, Graphs1-4), they have downward movement for several years before reversing for upward movement in all four districts considered in this research. A possible explanation of this yield-trend behavior is that rainfall also decreased simultaneously impacting the crop yield over the years before turning back upward and creating a climate cycle that resulted in v-shaped yield-trend pattern. Therefore, this climate change pattern is important information for explaining the association between crop yield and rainfall. Multiple regression models that controlled for this phenomenon (as dummy variable) to establish the degree of association between yield and rainfall are reported in Table1. All these regression models appeared to fit well in determining the co-relational association between the crop yield and rainfall. The best fitted model appears to be in "Yendi" with the highest coefficient of determination (R^2) 97.61% after corrected for autocorrelation, which is identified as second order autoregressive error model. These results indicate that linear relationship effect of March rainfall in general impact the crop yield positively. In addition, to control for diminishing effect of rainfall (as rainfall attains the higher level) on the crop yield we have included the quadratic term in the regression model. Thus, these regression results establish the fact that there exists a higher degree of association between rainfall and crop yield for implementing a rainfall based index insurance. Insurance payment is triggered when rainfall exceeds a predetermined threshold level towards the lower amount to indicate drought and therefore assumed crop loss. Since, drought is an effect of rainfall deficiency that results in crop loss, we would like to group (cluster) rainfalls that are associated with lower crop yields by applying cluster analysis.

Table 1: Regression results of yield on rainfall for four districts (1994-2007)

Dependent Variable (yield)	Intercept	Climate change cycle (dummy)	Rainfall	Rainfall Square	Model R-square	Corrected for Auto-Correlation
Tamale	0.2812 (0.4330)	0.1512 [yr2002] (.2390)	0.0423 (0.0544)	-0.0005 (.1296)	86. 50%	AR(1) [parameter significant at 2%]
Yendi	1.0586 (0.0001)	0.0600 [yr2000] (0.0829)	0.0049 (0.0438)	-0.00009 (0.0429)	97.61%	AR(2) [parameters significant at 1%]
Salaga	1.0829 (0.0003)	0.0173[yr2003] (0.8753)	0.0057 (0.3375)	-0.0001 (0.1679)	86.56%	AR(2) [parameters signf. at 1%&5%]
Damango	1.0706 (0.0001)	-0.7934[yr2002] (0.0001)	0.0171] (0.1821)	-0.000001 (0.9660)	88.23%	AR(none)

Model based clustering is applied to obtain rainfall threshold that could possibly signal trigger for payment as a proxy of crop loss. We run the model-based cluster analysis on the March rainfall data based on crop yield. Application of cluster analysis on the rainfall data with respect to yield using “mclust’ in “R” created two clusters. The rainfall trigger is obtained from the lower (red) cluster in the graph below that is generated by “R”, since the lower graph represents the lower amount of rainfall and lower yield combination. We define average rainfall in the lower (red) cluster (group) as threshold for trigger R_T to start payment assuming crop loss has occurred and R_S (stop-loss) as the minimum rainfall in the lower cluster as an indicator for full payment activation.



From the results of clustering we have obtained rainfall triggers, $R_T = 15.11$ and $R_S = 5.13$. Therefore, for an example of insured amount (IA) equal to \$100 dollars,

$$Payout = \begin{cases} 100; & R_A \leq 5.13 \\ 100\left(\dfrac{14.72 - R_A}{9.59}\right); & 5.13 < R_A \leq 15.11 \\ 0\,; & R_A > 15.11 \end{cases}$$

Thus, under normal distribution assumption the expected pay out becomes;

$$E(Pay\ out) = 100\int_{-\infty}^{5.13} f(R_A)\, d_{R_A} + \frac{100}{9.98}\int_{5.13}^{15.11} 15.11\, f(R_A) d_{R_A} - \frac{100}{9.98}\int_{5.13}^{15.11} R_A\, f(R_A) d_{R_A}$$

$$= 100\big(F(5.13)\big) + \frac{100}{9.98}\Big(R_T\big(F(15.11) - F(5.13)\big)\Big) - \frac{100}{9.98}\int_{5.13}^{15.11} R_A\, f(R_A) d_{R_A}$$

$$= 100(0.064712) + \frac{100}{9.98}\big(15.11(0.17954 - 0.064712)\big) - \frac{100}{9.98}(1.23024)$$

Hence, $E(Pay\ out) = 11.53$.
Since, $Premium = Present\ Value\ [E(Pay\ out)]$ and for one year contract (where, t=1) with 5% annual interest rate the premium is obtained as; $Premium = e^{-0.05}(11.53) = 10.97$.

CONCLUSION

This paper makes a number of significant contributions to the literature. It provides additional evidence that crop yield is affected by climate change and needs to be taken into account when establishing association between weather and crop yield to create index based insurance. In addition, it also provides evidence signifying cluster analysis as an objective method for creating rainfall trigger as in indicator for drought. However, the crop yield displays long memory and is therefore needed to be corrected for autocorrelation to establish the association through the regression model. These results, while important, are not unexpected given the farm management and practice that are similar from year to year and the climate change that appears as cycle due to external phenomena, such as, El Niño.

Farming usually tops the list among the agricultural practices that generate income for large percentage of people in Ghana. More specifically, farming represents 36 percent of the country's GDP and is the main source of income for more than 60 percent of the population. Agriculture in Ghana is highly dependent on rainfall and production fluctuates widely due to the weather variations over time. In recent years, along with other developing countries, weather variations and therefore climate change in Ghana have negatively impacted their agricultural economy. Since, drought is a recurring scenario; farmers should be encouraged to explore other methods of farming such as drought resistance seed in addition to other farm management techniques in order to decrease their exposure to crop loss.

In addition, a drought insurance program based on rainfall contracts could have potentially significant benefits to the farmers. In our paper objective trigger estimation was proposed and should minimize moral hazard and adverse selection risk and promote a rapid, and more structured pay-out process. Based on our analysis of rainfall and yield data across the districts, this study has determined that a rainfall based insurance product is feasible. The statistical correlation between rainfall and maize yield appears to be sufficiently strong in the districts considered in our analysis. Using data from a 14 year period, the trigger and stop-loss rainfall level was determined for all the districts together. These proportional contracts would pay the insurer an amount based on the shortfall of actual rainfall during a determined period compared to the trigger rainfall obtained from the cluster analysis, and the contracts could be purchased in any amount, allowing farmers to insure the full amount of their expected revenue loss. Accordingly, these results add another dimension in this field of research concerning the creation of rainfall trigger for weather-based index insurance that has differential effect on crop yield. Therefore, this study provides evidence for policy makers, society leaders, and financial institutions to understand the impact from some of the underlying forces such as, climate change on crop production and can become valuable information for future policy making process.

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