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

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Abstract: Farming often tops the list of agricultural practices that generate income for a large percentage of the population in developing countries, including Ghana. In Ghana, as in other developing countries, changes in weather patterns have negatively impacted crop yields. Traditional agricultural insurance can be a risk management mechanism to recover from these losses. However, traditional insurance has several drawbacks, including high administrative costs and moral hazard. An alternative would be index-based insurance, such as rainfall-based index insurance. Accordingly, developing an associative model that may include linear or non-linear relationships to establish a correlation of crop yield with rainfall may provide satisfactory results. In addition, the occurrence of a trigger that signals insurance payment due to drought is an important component in the pricing of drought-triggered index insurance. In that regard, we have introduced model-based cluster analysis for determining the drought trigger.

Agricultural practices are highly dependent on the specific timing of various climatic conditions for crop growth and crop yield. However, climate change, such as increasing frequency and severity of droughts or floods, could pose severe threats to agricultural practices. Therefore, the effect of climate change needs to be incorporated into the analysis, along with other factors that affect agricultural production. In our study, we have found evidence that crop yield is significantly affected by climate change and, therefore, has the potential for indicating much variation in crop production. [Key words: drought trigger, crop index insurance, climate change, premium calculation; JEL classification: G22, Q14, Q54, C38, O13.]

INTRODUCTION

Farming typically is at the top of the list of the agricultural practices that generate income for a large fraction of the world's population. In developing countries, agricultural practices are the main source of household

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income for maintaining their livelihood. In Ghana, as in other developing countries, the majority of the population depends on income from farming as their sole source of revenue. Recently, many countries of the world have experienced volatility in farming practices because of weather variations due to global climate change. Ghana's agricultural farming has also been negatively impacted by weather variations, with a negative impact on the agricultural economy (Etwire et al., 2013). These weather variations due to climate change have the capability to cause severe losses in agricultural income, including loss of crops and livestock, that forces these farmers into complete poverty and makes it difficult for them to reclaim their livelihood without any proper risk management mechanism. In addition, these income losses create an environment for sub-optimal management of financial risk, including choosing low-risk and low-return assets that limit growth potential, and in many cases lead to selling of assets at inopportune times. This issue is exacerbated by the reaction of lending institutions, which may limit lending to farmers in order to reduce exposure to agricultural risk. These indirect effects combined can hinder the overall economic growth of the entire country (Barnett et al., 2008). Furthermore, insurers may avoid underwriting policies that have positively correlated risks (Schoder et al., 2013).

Weather conditions have the ability to impact crop growth on varying levels and have the potential to influence crop yield. The effect of weather on crop yield also depends on other agronomic factors, such as fertilizer use, plant density, soil type, and soil condition. However, the amount of rainfall and pattern of rainfall affects water availability in the soil and therefore the crop growth pattern that is associated with crop yield (Denmead and Shaw, 1962). The amount of, timing of, and variations in rainfall during the crop growing season may be related to climatic factors. Similarly, the amount of rainfall during a given year has been shown to be associated with sea surface temperature (SST). El Niño is one of the natural anomalies that influence SST variations. El Niño is a naturally occurring phenomenon that causes fluctuations in SST and wind patterns across the equatorial Pacific Ocean. During an El Niño episode, the usual increase in SST of the tropical Pacific Ocean is 0.5° C to 0.9° C. In general, El Niño impacts weather through changes in seasonal rainfall patterns and amounts that can affect agriculture production.

In most cases, the relationship between water requirements and crop yield is based on a particular crop's sensitivity to water shortage during growing periods. In general, crops are more sensitive to water insufficiency during the emergence, flowering, and beginning of fruit development periods. Therefore, lack of rainfall or excessive rainfall at the wrong time in the growing season can significantly hinder crop growth and result in severe crop losses. However, farmers can manage the risk of these losses through agricultural insurance. It is one of the most useful tools for managing financial risks when farming. Because of high transaction costs that involve significant government subsidization, traditional agricultural insurance is difficult to implement, specifically in developing countries, and it may obstruct protection from risk (Skees, 2008b) to the farmers. In order for an insurance framework to be effective, purchasers of the insurance should perceive that the premiums and expected benefits offer value to them, while the sellers of the insurance also see opportunity for a positive actuarial (statistically reliable) result. An example of traditional agricultural insurance is "yield protection" (YP), which 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 a yield guarantee, based on regional average yield or on individual historic yield, where the main risks affecting yield (e.g., drought) are covered. This type of crop insurance relies on direct measurement of the loss or damage suffered by the farmer. In general, field loss measurement is usually expensive and resource prohibitive, particularly in areas that involve large numbers of small-scale farmers. This creates a challenge in the implementation process of traditional insurance.

In areas dealing with greater numbers of small-scale farms, index-based insurance instruments may be a better and more plausible alternative to traditional insurance. Index-based insurance is an insurance scheme that pays for losses based on an index, which is an independent measure that is presumed to be highly correlated with crop yield. One of the benefits of index insurance is that it attempts to prevent the moral hazard and insurance fraud issues (Skees, 2008b) that are prevalent in traditional insurance. Lesch and Baker (2013), using a consumer survey, identified factors contributing to the insurance fraud environment. As part of its commitment to lessen vulnerabilities of small-holders and open their access to financial services to improve their livelihoods, the International Fund for Agricultural Development (IFAD) has been working continuously on development and implementation of index insurance (IFAD and WFP, 2010). Accordingly, a weather-based index insurance will likely be an appropriate form of risk management in northern Ghana, especially because of the virtual absence of irrigation systems. Water stress has substantial potential for impacting crop production (Bannayan et al., 2008) and, therefore, crop yield. This is specifically noteworthy in regions where irrigation systems are nonexistent. Thus, developing a weather-based crop insurance, such as a drought trigger (Chantarat et al., 2007) for crop loss, may provide a suitable 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, including weather factors that result in drought, flood, and hail, which can impact crop yield and create variations in crop production. Thus, development of an associative modeling process to understand the crop yield patterns that account for yield variations over time is an objective for index formation. Various procedures, in the form of linear trend, quadratic trend, and polynomial trend (Just and Weninger, 1999; Cooper, 2010), have been explored by many researchers in order to de-trend the yield and isolate the real effect. A critical threshold (Prasad et al., 2006) that occurs due to external influences is also identified in many studies. Critical thresholds occur when the outcome of a process over time is not a single linear function of time, but changes abruptly at some threshold point. Agricultural management regime changes may have threshold-type effects on the response process. For example, a change in the type of fertilizer or amount of fertilizer applied due to environmental regulation or introduction of a government subsidy may cause a threshold in the crop yield outcome. In addition, other non-linear methods, such as piecewise regression have been applied and found to be useful for understanding crop yield patterns (Skees et al., 1997; Choudhury et al., 2015).

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 indicates observation of the intensity of indirect environmental effects on our food sources (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 a statistically significant association between crop yield and rainfall, and calls for implementing feasible rainfall-based index insurance.

INDEX-BASED INSURANCE

Index-based insurance is an agricultural insurance scheme that pays for losses based on an index. Index-based insurance is an independent and objective measure that is highly correlated with losses. Weather-related indexed insurance payment is based on realization of a 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 socioeconomic development. Weather devastation can trap farmers and households in poverty; on the other hand, the risk of such shock also limits the willingness of farmers to invest in measures that may increase their crop outcome and help improve their economic environment.

Numerous 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 the USA and the measures taken to rescue the crop insurance program. Much of the interest in area-based yield insurance has been motivated by concerns about and limitations of traditional individual farm-loss crop insurance (Skees, 2008a; 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 small-scale farmers. However, other potential target groups may be aggregated villagers and commercial farmers.

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

(1) 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 manage low-to-medium-frequency covariate risks such as drought.
(2) Index-based insurance can provide an alternative method of funding for disaster recovery assistance programs and may be a requirement for loan approval processes by financial institutions.

WEATHER AND CLIMATE CHANGE EFFECT

Daily atmospheric occurrences are connected to "weather" and "climate." Atmospheric fluctuations occurring hour to hour and day to day make up the *weather*. Atmospheric factors 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 average conditions and anomalous weather conditions for a particular geographic region over long periods of time.

Both weather and climate have been shown to affect crop growth and crop yield. Availability of water is 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, which has the potential to reduce crop production. If the rainfall amount is insufficient for a specific growth period and persists during the growing season, crop production will very likely suffer. If this phenomenon occurs repeatedly and over prolonged periods of time, it is a likely indication of climate change.

Agricultural practices are highly dependent on the specific timing of various climatic conditions for crop growth and consequently crop yield. In general, increases in precipitation up to a certain level can be beneficial for crop production. However, climate changes such as increasing frequency and severity of droughts or floods could impose severe threats to agricultural practices. As a result, climate change can pose challenging conditions for crop cultivation and yield (Carriquiry and Osgood, 2012). Therefore, the effect of climate change needs to be considered along with other factors that affect agricultural production, such as farming environment, farming practices, and application of technology. Consequently, trying to understand the effect of climate change on our food supply is a worthy endeavor. Given the multi-layered nature of elements of climate change, identifying the effect of climate change on our food supply can be a very complex and daunting task. Many mainstream 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 could have significant effects on crop productivity, including increased inter-annual climate variability associated with phenomena like El Niño. Atmospheric phenomena such as El Niño, which have been shown to affect temperature and precipitation, can increase the frequency and intensity of extreme weather and usually persist for several years (Moy et al., 2002; Trenberth, 1997). Consequently, this phenomenon has great potential to manifest climate change and has significant impact on crop yield. As a result, it is worthwhile to determine the degree of association between crop yield and precipitation as related to all aspects of climate change.

RESEARCH METHODOLOGY

Associative models relating crop yield with explanatory variables such as rainfall can be used to estimate crop production. Similarly, univariate time series forecasting methods can be applied for crop yield prediction (Choudhury and Jones, 2014). The associative model's performance generally improves after trends are removed. Many researchers identify proper statistical techniques that may effectively remove or at least reduce the trend effect before further analysis. By applying a trend elimination process, an absolute relationship between crop yield and weather factors is established. To understand crop yield patterns better it is important to identify relevant external factors that influence crop yield. Data that are collected from the field are typically very noisy, and relationships with other factors are generally uncertain due to numerous variations incorporated into the process. To reduce these variations, we have used the three-period moving average, MA (3), smoothing technique, so the yield pattern and its trend are easily identifiable. To formulate a proper response function we allow for the diminishing effect of water requirements for an increase in growth and therefore crop yield. Thus, the higher the rainfall amount, the higher the yield outcome, until a saturation point is reached beyond which any more rainfall will not improve the yield. Therefore, it is advisable to formulate the response function as a quadratic equation.

Data for this research were collected from the Ministry of Food and Agriculture, a government organization in Ghana. The statistical department under the Food and Agriculture ministry is an independent government organization that is responsible for collecting and compiling official statistics in Ghana. Crop yields are reported in metric tons of crop production per hectare, which is the ratio of total production in a district divided by total land cultivated in that district. The districts are the administrative units at which most socioeconomic and agricultural statistics are collected. Rainfall data, reported in millimeters, were obtained from rainfall stations at the district level.

Researchers modeling both crop yield and climate and weather have conducted a robust array of research to identify the effects of weather factors and the uncertainty they generate with regard to crop production. Specifically, weather conditions can be a source of uncertainty in crop production and yield when considering farming in large areas. The models that deal with crop yield primarily concentrate on soil condition (Pachepsky and Acock, 1998) and various weather factors to explain the uncertainties in the yield. Climate model researchers focus on identifying the weather conditions and variations that affect crop production and quantify crop yield based on climate change scenarios (Hoogenboom, 2000; Mearns et al., 2001; Semenov and Porter, 1995). When considering large-area farming, such as by province or district, weather factors are more relevant to crop yield uncertainties than soil variations (Etwire et al., 2013; Hansen and Indeje, 2004; Jones et al., 2000). Our research is concentrated on data from the northern region of Ghana, which is considered to be the major breadbasket of the country. This region of Ghana is also predisposed to weather variations, specifically, to lack of rainfall. All agricultural practices in Ghana, including farming, are almost entirely reliant on rainfall (Stutley, 2010) for water needs. Consequently, our study will attempt to create a 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 insurance payments 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 the indication of crop loss. We introduce model-based clustering as an approach for determining an optimal rainfall trigger for drought identification. Drought may be defined and characterized in many ways (Skees et al., 2001). However, drought in general is an effect of rainfall (water) deficiency and thus results in crop loss due to its 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 a cluster analysis approach to separate rainfall into groups with similar 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 others within the cluster with respect to some criterion. 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; it 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 each cluster will be close together and different clusters will be far apart. Cluster analysis, similar to factor analysis, makes no distinction between dependent and independent variables (or factors). The entire set of observations forms an 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 a model-based clustering process (Fraley and 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 a weather factor, such as rainfall. The weather-based insurance instrument is developed in such a way that when rainfall exceeds a predetermined threshold, payment is triggered, and the payment structure can be proportionate to an index beyond the threshold or to 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, issuers and policyholders of index-based insurance are exposed to the basis risk. For example, it is possible for the issuers of a temperature-based (Okhrin et al., 2013) or rainfall-based indexed insurance policy to experience production loss and yet not be eligible to receive a payment because there has been no occurrence of the trigger for excessive temperature or rainfall shortage. Similarly, it is possible for a policyholder 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 climate change information into the weather-yield association model has the potential to improve the effectiveness of weather-based index insurance. In establishing this relationship it is critical to consider the rainfall needs for optimal growth at different stages of the 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 actual rainfall with a predetermined threshold for crop loss.

Pricing and Payment Structure for Drought Insurance

Consider a rainfall index insurance that pays the entire Insured Amount (IA) if actual rainfall R_A in March drops below the stop-loss rainfall R_S, pays the proportional $IA\left(\frac{R_T - R_A}{R_T - R_S}\right)$ when the actual rainfall R_A is between the trigger rainfall R_T and stop-loss rainfall R_S, and pays nothing when the actual rainfall R_A exceeds the trigger rainfall R_T, as shown in Figure 1.

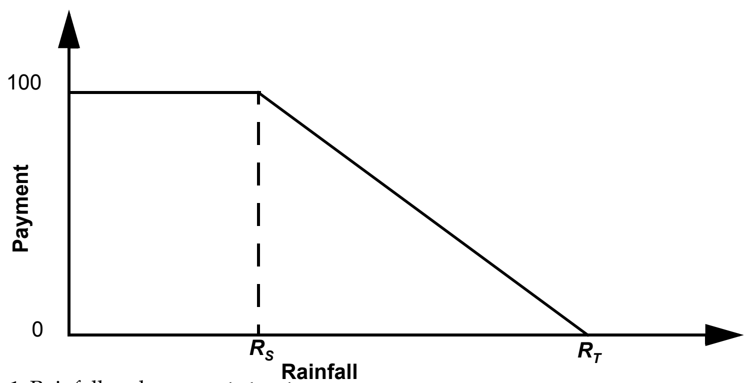

Fig. 1. Rainfall and payment structure.

From the payment structure in Figure 1, the insurance payment can be expressed as,

$$Payout = \begin{cases} IA, & if\ R_A \le R_S \\ IA\left(\frac{R_T - R_A}{R_T - R_S}\right), & if\ R_S < R_A \le R_T \\ 0, & if\ R_A > R_T \end{cases} .$$

As a result,

$$E(Payout) = IA(F(R_S)) + \frac{IA}{R_T - R_S}(R_T(F(R_T) - F(R_S))) - \frac{IA}{R_T - R_S}\int_{R_S}^{R_T} R_A f(R_A) d_{R_A} .$$

We can therefore express *Premium as Present Value* [E($Payout$)]. Therefore,

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

EMPIRICAL RESULTS

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 breadbasket of the country, and it is also the region most susceptible to weather and climate change, especially recurring lack of rainfall.

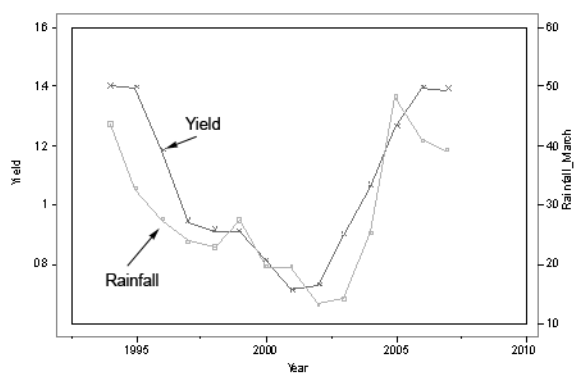

Fig. 2. Plot of yield and rainfall in Tamale.

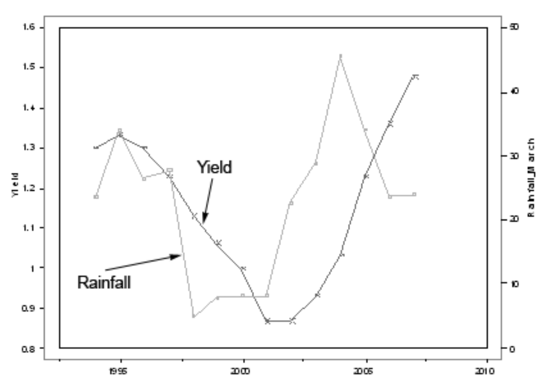

Fig. 3. Plot of yield and rainfall in Yendi.

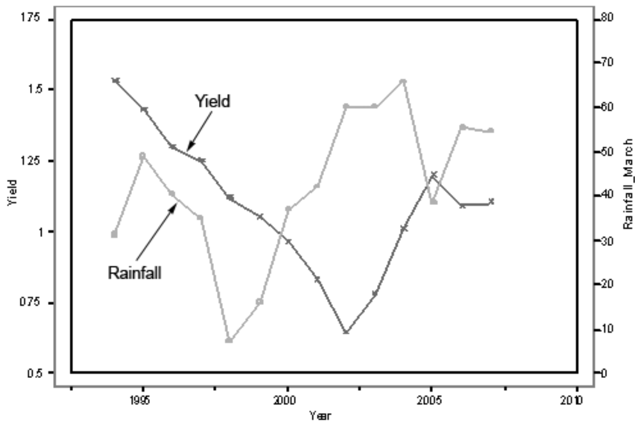

Fig. 4. Plot of yield and rainfall in Salaga.

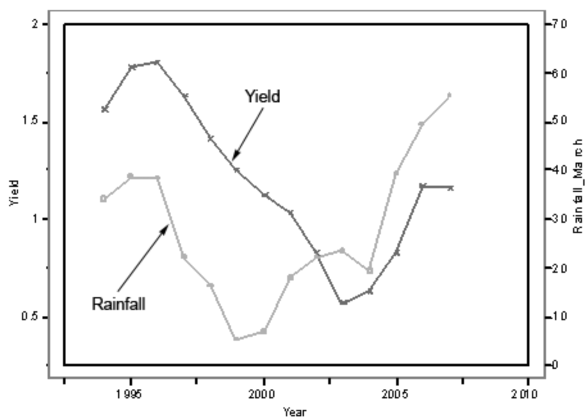

Fig. 5. Plot of yield and rainfall in Damango.

The trends in yield for four different districts demonstrate that the trends are not linearly related with respect to time (see Figs. 2–5); they have downward movement for several years before reversing to upward movement in all four districts. A possible explanation of this yield-trend behavior is that rainfall also decreased concurrently, 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.

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] (0.2390)	0.0423 (0.0544)	–0.0005 (0.1296)	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)

Multiple regression models that controlled for this phenomenon (as a dummy variable) to establish the degree of association between yield and rainfall are reported in Table 1. All these regression models appeared to fit well in determining the co-relational association between crop yield and rainfall. The best-fitted model appears to be in "Yendi," with the highest coefficient of determination (R^2) 97.61% after correction for autocorrelation, which is identified as second-order autoregressive error model. These results indicate that the linear relationship effect of March rainfall in general impacts the crop yield positively. In addition, to control for the diminishing effect of rainfall (as rainfall attains a 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, though non-linear, for implementing 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) rainfall amounts that are associated with lower crop yields by applying cluster analysis.

Model-based clustering is applied to obtain a rainfall threshold that could possibly signal a trigger for payment as a proxy for 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 (Fig. 6). The rainfall trigger is obtained from the lower cluster (hollow-square in Fig. 6) that is generated by "R," since the lower cluster represents the lower amount of rainfall and lower yield combination. We define average rainfall in the lower cluster

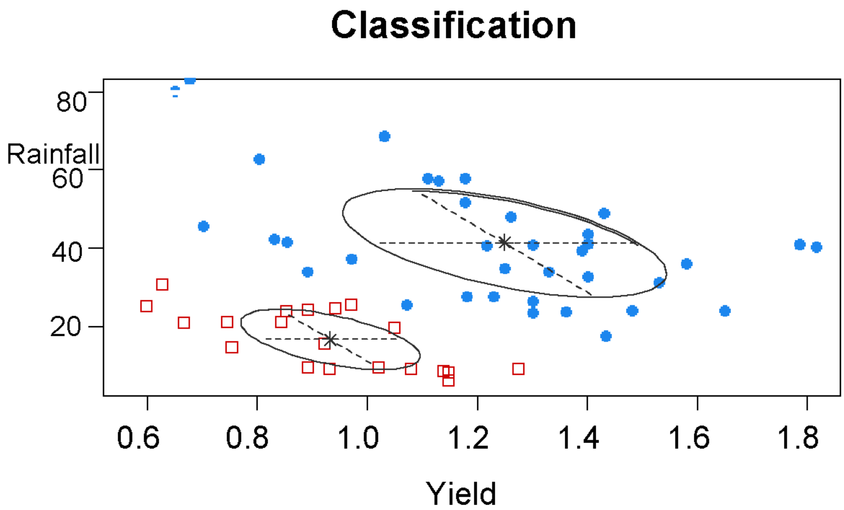

Fig. 6. Cluster analysis of rainfall.

(hollow-square) as the threshold for trigger R_T to start insurance payment, assuming crop loss has occurred, and R_S (stop-loss) as the minimum rainfall amount in the lower cluster as an indicator for full payment activation.

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

$$Payout = \begin{cases} 100; & if \;\; R_A \leq 5.13 \\ 100\left(\dfrac{15.11 - R_A}{9.98}\right); & if \;\; 5.13 < R_A \leq 15.11 \\ 0; & if \;\; R_A > 15.11 \end{cases} .$$

Thus, the *expected payout* can be calculated based on the above payment structure and consequently the *insurance premium*.

CONCLUSION

This paper makes a number of significant contributions to the literature related to weather-based index insurance. It provides additional evidence that crop production is affected by climate change and needs to be taken into consideration when establishing the association between weather factors and crop yield to create index insurance. However, crop yield displays long memory and therefore needs to be corrected for autocorrelation. In addition, it also provides evidence signifying cluster analysis as an objective method for creating a rainfall trigger as an indicator for drought. These results, while important, are not unexpected given that farm management and practices are similar from year to year, and the climate change that appears as cycle is an external phenomenon.

Farming is the main source of income for a majority of the population in Ghana. Therefore, income from farming is very important for the economic stability of Ghana. Agriculture in Ghana is highly dependent on rainfall, and without the presence of irrigation systems, crop production fluctuates widely over time due to weather variations. In recent years, weather variations indicating climate change in Ghana, along with other developing countries, have negatively impacted their agricultural economy. Since drought is a recurring scenario, farmers should be encouraged to explore other kinds of farming practices, such as drought resistant seed and other farm management techniques, in order to reduce their exposure to crop loss and to minimize the risk. Additionally, a drought insurance program based on rainfall contracts could add significant benefits to the farmers.

In our paper, an objective trigger estimation for index insurance was proposed, which should minimize moral hazard and adverse selection risk and promote a rapid, more structured payout process. Based on our analysis of rainfall and yield data across the districts, this study has determined that a rainfall-based index 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 in creating a rainfall trigger for weather-based index insurance. Therefore, this study provides evidence for policy makers and financial institutions to understand the impact of some underlying forces such as climate change, on crop production and can become valuable information source for future policy making processes.

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