# ASSOCIATION OF RAINFALL AND DETRENDED CROP YIELD BASED ON PIECEWISE REGRESSION FOR AGRICULTURAL INSURANCE

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**ABSTRACT**

*Agricultural insurance 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 high transaction costs and other challenges that may hinder the protection from risk. An index based insurance is more likely to be a superior and viable alternative to traditional insurances for many developing countries because of its independent and objective nature. Various weather related factors are one of the major uncertainties that effect crop growth and yield. In order to develop an effective weather based insurance model, crop yield needs to be correlated with the weather factor(s) such as rainfall. However, crop yield pattern may be dependent on other external factors and in general create an increasing or decreasing trend in the yield. In our analysis, we observe that both downtrend and uptrend exists in our crop yield data with a threshold in the middle and thus creates a rare trend pattern that is cyclical. In order to identify the explicit relationship between yield and rainfall, we detrended crop yield by using piecewise regression. In addition, crop yield data that are collected from the field are usually noisy and the relationship between weather factors and yield responses are in general weak. Thus, a three-period moving average smoothing technique was applied on the data to make the pattern of the trend more visible. Consequently, identification of proper trend pattern, such as, cyclical-trend rather than a simple linear trend for detrending the crop yield appeared to be significant in this research study. As a result, our study adds significant contribution in this field of research concerning the influence of unobservable factor(s) on the crop yield that creates threshold effect. The implication of these findings in this study is significant for developing an appropriate associative model for creating weather based index insurance.*

# INTRODUCTION

Agricultural practices are main source of income for the large percentage of the population in developing countries. Farming usually tops the list among the agricultural practices that generate income for the majority 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, economic growth in agricultural sectors in Ghana has surpassed growth in the non-agricultural sectors. Income from agricultural sectors have expanded by an average annual rate of 5.5 percent compared to 5.2 percent overall growth of the whole economy (Bogetic et al., 2007). Along with other developing countries, climate changes 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 left 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 assets and activity portfolios that reduce the risk of greater suffering, that limit growth potential and investment incentives. This situation deteriorates more by reduction in nutrient intake, withdrawing of children from school, and hiring them out to work. The problem exacerbates further by the reaction of financial institutions and by their decision to restrict lending to farmers in order to minimize exposure of financial risk. All of these consequences collectively hinder overall economic growth (Barnett et al., 2008).

One of the major factor that may have varying impact on crop growth and crop yield is weather. However, the weather related effects on crop growth and crop yield depends on other agronomic factors, such as, fertilizer use, plant density, soil type, and soil condition. One of the major weather conditions that have an impact on crop yield is the amount of rainfall received during growing season (availability of water for regions without any access to irrigation). In many parts of the world rainfall amount affect water availability in the soil, crop type, growth patterns of crops, and yield outcome of crops (Al-Kaisi & Broner, 2011). The relationship between water availability and yield outcome is depended upon the particular crop's sensitivity to water deficiency during growth stages. In general, crops are more sensitive to water deficiency during emergence, flowering, and early fruit formation stages. Consequently, amount and timing of rainfall can cause heavy crop losses for farmers. One way, in which farmers can deal with these losses is through agricultural insurance. It has been 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 and other challenges that may hinder the protection from risk for financial institutions (Skees, 2008). In order for an insurance 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 insurance is a "yield insurance" that provides yield guarantee, based on regional average yield or on individual historic yield, where the main risks affecting yield (e.g. drought) are comprised. In developed countries such as USA, this type of insurance is also called combined or multi-peril insurance. This type of traditional crop insurance relies on direct measurement of the loss or damage suffered by an individual farmer. However, field loss assessment is normally costly or not feasible, particularly where there are large numbers of small-scale farmers or where insurance markets are undeveloped and creates a challenge in the implementation process.

An alternative to traditional insurance is index based insurance instruments. Index based insurance is an agricultural insurance system that pays for losses based on an index, an independent and objective measure that is very much correlated with crop losses due to extreme weather. Index insurance contracts, such as rainfall insurance, attempt to circumvent the moral hazard and adverse selection problems that plague traditional insurance (Skees, 2008). International Research Institute (IRI) for Climate and Society at Columbia University (Hellmuth et. al., 2009) quotes United Nations Secretary General Kofi Annan "As an innovation, index insurance may hold answers for some of the more obstinate problems faced by the poor and the vulnerable." The International Fund for Agricultural Development (IFAD) has been working for many years on index insurance as part of its commitment to reduce vulnerabilities faced by rural smallholders and open their access to a range of financial services with the sole aim of improving their livelihoods (IFAD and WFP, 2010).

In general, average crop yield is expected to stay same over time if there is no technological change (improvement or deterioration) or policy change that may impact crop yield differently. However, other external changes, such as, weather factors (e.g., drought, flood, hail, etc.) can impact the crop yield and may change the average crop yield over time. The primary purpose of crop insurance is to provide protection for farmers against yield shortfalls due to external factors. As a result, an associative modeling process to understand the crop yield pattern that accounts for yield variations over time is a preferable method. Researchers have explored various procedures, such as linear trend, quadratic trend, polynomial trend (see, Just and Weninger**,** 1999; Cooper, 2010) in order to detrend the crop yield over time. 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). Several studies have identified critical thresholds (Prasad et al. 2006) that occur due to external influences to improve their model's performance. 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. Abrupt changes in the response outcome can also occur in other systems. Changes in management regimes may have threshold type effects if response processes are viewed over time. For example, a change in chemical (fertilizer) application due to environmental regulation may cause a threshold in the long-term crop yield dynamics. In this paper we apply piecewise-regression model to detrend crop yield data that are effective in modeling abrupt threshold.

## DATA AND RESEARCH METHODOLOGY

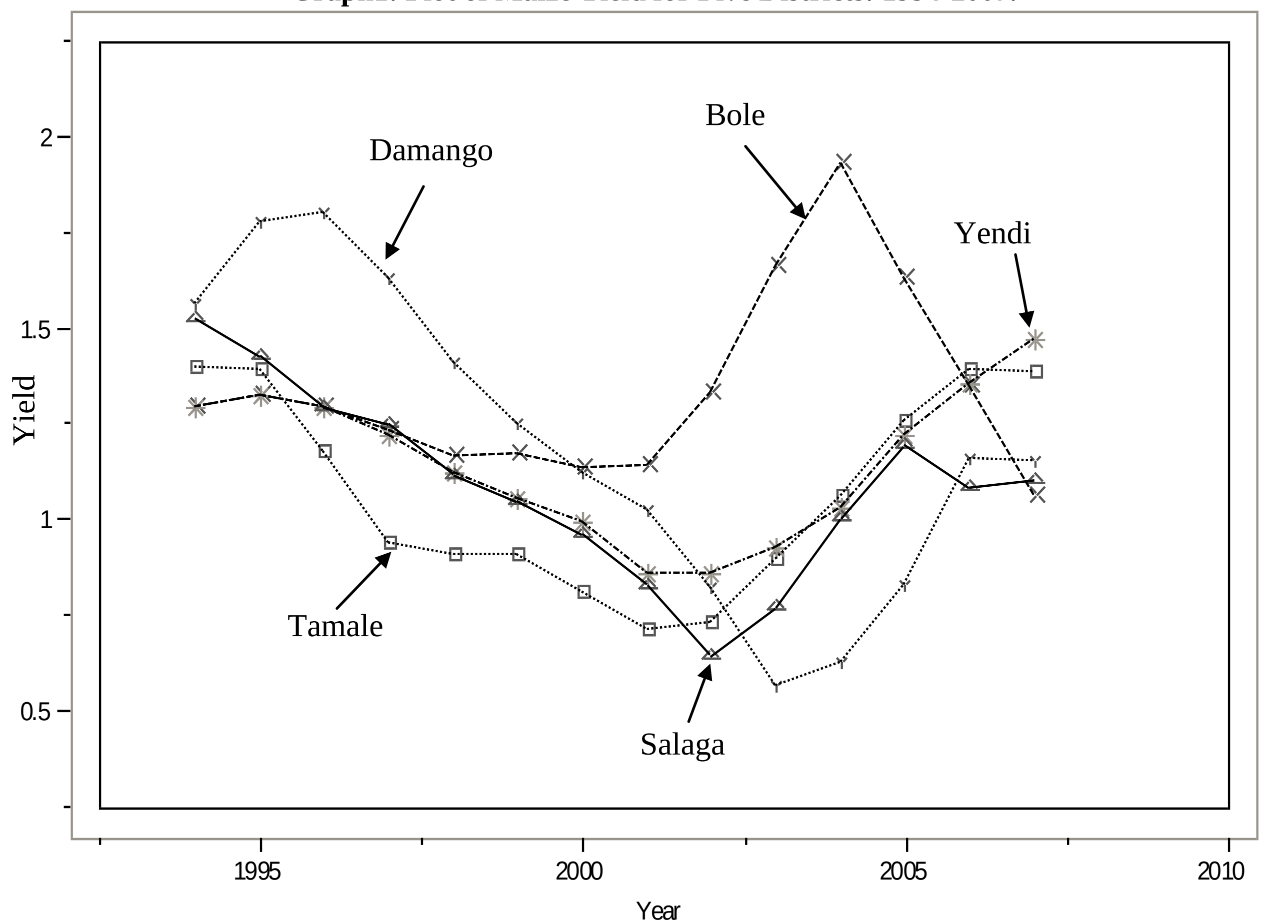
Crops that are likely to be suitable for weather based index insurance include rain-fed maize and rice. Crop yield estimation can be done with crop simulation models or empirical associative statistical models relating crop yield with explanatory variables, such as rainfall. These associative models performance generally improve after trends are eliminated from the crop yield. Therefore, the primary focus of this paper is to provide a statistical technique that may effectively eliminate or at least reduce the unknown trend effect from the crop yield. By using this 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 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 address this variations, we have used three-period moving average (MA (3)) smoothing technique both for the crop yield and the rainfall data, 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 monotonically increasing nature of the yield response function. We also assume that the higher the rainfall amount, the higher the yield, until at some point the added rainfall reach a saturation point and does not improve the yield further. Therefore, we formulate the response function as a quadratic equation whenever feasible. To be specific, we formulated the response function as either linear or quadratic function of rainfall on the detrended yield. We carried out the detrending of yield by applying piecewise regression.

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 in 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). Northern region of Ghana is considered to be the major bread basket of the country and therefore our research is concentrated in 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 maize production in five districts from the northern part of Ghana to correlate crop yield with rainfall over time.

**Graph1: Plot of Maize Yield for Five Districts: 1994-2007.**



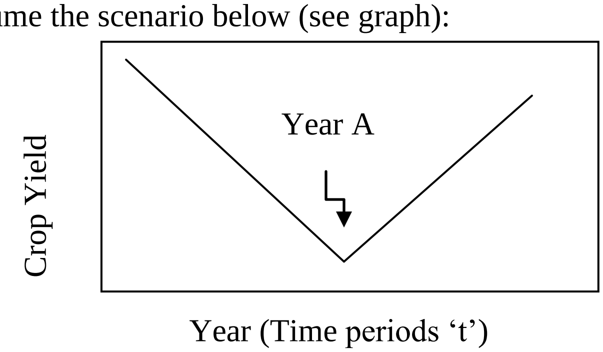

Graph-1 presents plot of crop yields for five different districts. These yield plots over time exhibit some similar patterns of downward trend for the beginning years and upward trend pattern for the last several years. These districts ended their downtrend of yield around year 2002/2003. Thus, the breakpoint for piecewise regression is identified as year 2002/2003 depending on the district. To unravel these complex trend movements in the yield, we developed piecewise regression models to detrend the yield data that are applied separately to each district to capture the specific trend pattern for that district. This method was applied to observe the real relationship between crop yield and rainfall without the influence of possible external factors on the yield. The following paragraphs describe the concept of piecewise regression model briefly, which we have implemented in our research study for the purpose of detrending the crop yield.

**Piecewise Regression**

Crop production and subsequently the crop yield processes are influenced by a number of factors, including spatial and temporal variability in crop growth. Variations in crop production have been attributed to fluctuations occurring by several external factors, including weather (Hansen & Indeje, 2004; Jones et.al, 2000), the soil condition (Serraj & Sinclair, 2002; Lecoeur & Sinclair, 1996), and the management practices (Moran, et al., 1997; Lobell & Asner, 2003). As a result, crop yield can exhibit exceptionally high variability, often up to an order of magnitude or greater in a given year. However, when yields are smoothed for a shorter time period, then they are relatively predictable patterns that appear in many situations. In many cases crop yield variations over time can be modeled as linear trend, quadratic trend, or polynomial trend that have been explored by researchers (see, Just & Weninger**,** 1999). Piecewise regression model have been found to be useful (see, Skees et al., 1997) when critical threshold is present in yield pattern.

When analyzing a relationship of crop yield over time, *t*, it may be apparent that for different ranges of *t*, different linear relationships occur for the yield. In addition to technological changes, these could also be due to government policy change to improve agricultural productivity. In these cases, a single linear function may not provide an adequate specification of the function. Piecewise linear regression may be a better representative function that allows multiple linear (or nonlinear) models to be fit to the data for different ranges of time. Breakpoints are the values of *t* (time) where the slope of the linear function changes (see, graph below). The value of the breakpoint may or may not be known in advance. In this study, breakpoint t (year A) is assumed to be known, although they are not same for all districts.

In other words, relationships that has different direction or magnitude of slopes at different time segments in the response variable with time, can be modeled using piecewise linear segments of models combined together that has different slopes for different time segments. Let us assume the scenario below (see graph):



The combined piecewise model can be expressed as:

$$Y_t = \beta_0 + \beta_1 T_{1t} + \beta_2 (T_{1t} - A) T_{2t} + \varepsilon_t \qquad \text{…. (1)}$$

Where, $T_{1t}$ = time trend (years: 1, 2, …, t), and

$$T_{2t} = \begin{cases} 1, & if\ T_{1t} > year\ A \\ 0, & if\ T_{1t} \leq year\ A \end{cases}$$

(see, Mendenhall & Sincich, 1996; McGee & Carleton, 1970).

Therefore, when year is less than or equal to "A" the equation (1) becomes:

$Y_t = \beta_0 + \beta_1 T_{1t} + \varepsilon_t$ , which is the first segment (or piece).

The second segment is obtained when year is greater than "A" and the equation (1) becomes:

$Y_t = (\beta_0 - A\beta_2) + (\beta_1 + \beta_2) T_{1t} + \varepsilon_t$ .

Consequently, we expect $\beta_1$ to be negative (which is the slope of the first segment) and $(\beta_1 + \beta_2)$ to be positive (which is the slope of the second segment) in the above scenario. Therefore, we expect $(\beta_2 > \beta_1)$ in absolute value.

To observe the relationship between crop yield and rainfall; two separate analyses were performed. First, we applied piecewise regression on crop yield using threshold factor (breakpoint) to estimate the trend that can be used to detrend the yield. Then, detrended yield (crop yield adjusted for trend) is regressed on the predictor rainfall to observe the association of crop production behavior. It is expected that increase in rainfall should increase the crop production, since higher amount of water will be capitalized into a higher amount of crop production. In addition to the linear rainfall factor (rainfall amount in a month), we have also explored quadratic rainfall factor to observe the effect of more rainfall amount on the crop yield. Even though, increase in rainfall amount should increase the crop production, and thus increase crop yield; however, the effect of additional rainfall amount diminishes as they reach a certain saturation point. Therefore, these relationships between crop yield and rainfall amount do not appear to be linear and therefore may be better captured by introducing a quadratic term in the model. Thus, we introduce a quadratic equation to understand the associative behavior of crop yield with rainfall. To test these hypotheses, two separate regression models were estimated in this research study.

Specification of the final regression model is of the following form (Month of rainfall may be different depending on the district):

$$Detrended\ Yield = \beta_0 + \beta_1 Rain\ Month + \beta_2 Rain\_sq\ Month \qquad \text{........... (2)}$$

Where:
***Detrended Yield:*** Amount of yield per hectare (three year moving average) that is detrended using the results from piecewise regression.
***Rain Month:*** Amount of rainfall in a specific month, e.g., March or some other month(s) (using three year moving average of rainfall) depends on the district.
***Rain_sq Month:*** Amount of rainfall square in a specific month (using three year moving average of rainfall).

Thus, two sets of regression models were run in two steps using SAS software (see, SAS/STAT User's Guide, 1993) on relevant factors to understand the associative nature of rainfall and yield. These analyses after controlling for external factors effect are to observe the differential effect of the crop yield due to rainfall occurrence at specific time (month) of the year due to different districts (or regions). Therefore, this research structure is designed to test the hypothesis that crop yield fluctuation is rainfall, time of the year, and location dependent.

**TABLE 1: Regression results of Detrended Yield for Bole.**
**(Corrected for autocorrelation – using Maximum Likelihood Estimates)**

| Variables | DF | Parameter Estimates | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | -0.2243 | 0.0728 | -3.08 | 0.0131 |
| **March Rain** | 1 | 0.006444 | 0.001880 | 3.43 | 0.0075 |
| **R-Square** | 0.5664 | | | | |

Note: The regression residuals model is identified as, $\left(1-\phi_1 B-\phi_2 B^2\right)\nu_t=\varepsilon_t$ and the estimated first and second order autoregressive (AR) parameters from SAS are, $\underset{(-4.01)^{***}}{\left(1-0.8199\,B\right.}\;\underset{(3.86)^{***}}{\left.+0.7892\,B^2\right)}\nu_t=\varepsilon_t$.

Autoregressive parameter's t-statistics are reported in the parentheses. They are both significant at the one (***) percent level of significance.

## EMPIRICAL RESULTS

There is a visible similarities in crop yield trend pattern over time among the districts (see, Graph-1), they exhibit some downward trend pattern in the beginning periods and then followed by upward trend pattern for the other years (except for Bole). This suggests that due to some unobservable phenomena crop yield may differ in different time periods and continues a downtrend or uptrend up to a certain threshold point before reversing. In addition, there are slight differences in declining trend segment's breakpoint at a different year for different districts. Therefore, it appears that there are two opposite directional trends in crop yields are in play which creates the crop yield trend-cycle that split up at a breakpoint around the year 2002/2003.

It is possible that this may be due to a weather cycle and/or management practice change or some other unobservable source of similar nature and this effect may also be location (geographic) specific. Therefore, we have analyzed our data for each district separately to isolate the location specific outcome. Thus, the idea of this study is to understand and observe explicit relationship between crop yield (detrended) and weather factor "rainfall" (water need), such that, the association effect of unobserved external factors on crop yield is eliminated through piecewise regression modeling process. The following results address the finding of our research study on the detrended crop yields' relationship with rainfall in different districts.

**TABLE 2: Regression results of Detrended Yield for Tamale.**

| Variables | DF | Parameter Estimates | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | -0.74233 | 0.26761 | -2.77 | 0.0197 |
| **July Rain** | 1 | 0.00850 | 0.00341 | 2.49 | 0.0318 |
| **July Rain_sq** | 1 | -0.00002257 | 0.00001014 | -2.22 | 0.0503 |
| **R-Square** | 0.6062 | | | | |

Piecewise regression models that are used in step one to estimate the trend-cycle component fit well with higher coefficient of determinations except for the Bole district (regression results' tables are not reported). Among all the districts "Damango" has the best fitted piecewise regression model with the highest $R^2$=0.9630 followed by $R^2$ of 0.9215, 0.8978, 0.8863, and 0.0999 for districts "Tamale", "Yendi", "Salaga, and "Bole" respectively. These piecewise regression models largely explain the variations due to unknown trend-cycle effect on the yield for most of the districts. Thus, our research results show that piecewise regression model provides better estimate for trend pattern in crop yield at a district level in this geographic region compared to other simple linear models and was an important tool to detrend the yield.

**TABLE 3: Regression results of Detrended Yield for Yendi.**
**(After corrected for autocorrelation – using Maximum Likelihood Estimates)**

| Variables | DF | Parameter Estimates | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | -0.0105 | 0.0296 | -0.35 | 0.7312 |
| **March Rain** | 1 | 0.0101 | 0.003101 | 3.25 | 0.0100 |
| **March Rain_sq** | 1 | -0.000331 | 0.0000674 | -4.90 | 0.0008 |
| **R-Square** | 0.8893 | | | | |

Note: The regression residuals model is identified as, $(1-\phi_1 B)\nu_t = \varepsilon_t$ and the estimated first and second order autoregressive (AR) parameters from SAS are, $\underset{(2.52)^{**}}{(1+0.6436B)}\nu_t = \varepsilon_t$.

Autoregressive parameter's t-statistics are reported in the parentheses. It is significant at the five (**) percent level of significance.

Multiple regression results of detrended yield on rainfall are reported in Tables1-Table5. All these models appeared to fit well in determining the relationship between the crop yield and rainfall. The best fitted model appears to be in "Yendi" with the highest coefficient of determination ($R^2$) 0.8893 after corrected for autocorrelation, which is identified as first order autoregressive error model (see, Table 3). These results indicate that March rainfall in general impact the crop yield positively. However, to control for diminishing effect of rainfall on the crop yield we have included the quadratic term in the regression model and the results show that our hypothesis of lesser effect of additional rainfall is established. However, timing of rainfall does not seem to affect crop yield equally among the districts. As for example, April rainfall seem to be a better predictor for "Salaga" (see, Table 4) with a moderate coefficient of determination ($R^2$) 0.3357. On the other hand, better condition for crop yield improvement by rainfall is July for "Tamale" and "Damango" (see, Tables 2 and 5). Thus, our analysis reveals that there are differences in rainfall effect on the crop yield that are geographic location (districts) dependent.

**TABLE 4: Regression results of Detrended Yield for Salaga.**

| Variables | DF | Parameter Estimates | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | -0.17021 | 0.07425 | -2.29 | 0.0426 |
| **April Rain** | 1 | 0.00146 | 0.000619 | 2.36 | 0.0380 |
| **R-Square** | 0.3357 | | | | |

**TABLE 5: Regression results of Detrended Yield for Damango.**

| Variables | DF | Parameter Estimates | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | -1.72795 | 0.53754 | -3.21 | 0.0093 |
| **July Rain** | 1 | 0.03087 | 0.00955 | 3.23 | 0.0090 |
| **July Rain_sq** | 1 | -0.00013301 | 0.00004118 | -3.23 | 0.0090 |
| **R-Square** | 0.5113 | | | | |

## CONCLUSION

We made significant contribution in understanding and implementation of detrending process of crop yield pattern in this literature. This research provides additional evidence of differential effect of rainfall on crop yield with respect to timing of rainfall and location of crop harvest (districts). It is apparent in this study that in addition to plant characteristics external factors such as, timing of measurable rainfall also affect crop yield. Specifically, we observe that a crop yield trend-cycle does exist in most of our data sets, which starts with the downtrend that ended around 2002/2003 and then reverse to an uptrend for next several years that creates a crop yield trend-cycle. This suggests that crop yield trend pattern is likely to be a cyclical pattern rather than a linear trend for this region. A possible explanation for this time dependent trend cycle of crop yield may be attributed to change in the weather pattern and/or change in management practices.

Consequently, these results add another dimension in this field of research concerning the effect of unknown factor(s) on the crop yield that has threshold effect. In addition, identification of proper trend pattern, such as, cyclical trend (uptrend and downtrend combined) rather than a simple linear trend for detrending the crop yield appears to be significant in this research. For a successful operation of weather based index insurance policy to work, the crops grown in different locations (districts) need to be properly detrended. Additional research study will be helpful, particularly with regard to the linkage between these factors and crop yield dynamics. To determine the length of downtrend or uptrend to understand the cause of trend cycle of crop yield, future research could examine some phenomena, such as, weather pattern change over different time periods. However, the power of piecewise regression model that was applied in this paper to eliminate the presence of crop yield trend-cycle does not depend on identifying the relevant factor(s).

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