Effect of Climate Change on Sugarcane Yield in Pakistan: A District Level Analysis

By

Zeeshan Mustafa

Supervised by
Dr. Muhammad Iqbal

DEPARTMENT OF ENVIRONMENTAL ECONOMICS
PAKISTAN INSTITUTE OF DEVELOPMENT ECONOMICS
ISLAMABAD, PAKISTAN

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Certificate

This is to certify that this dissertation by Zeeshan Mustafa is accepted in its present form by the Department of Environmental Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the thesis requirements for the degree of Masters of Philosophy in Environmental Economics.

Supervisor: ____________________________

Dr. Muhammad Iqbal
Chief of Research
Pakistan Institute of
Development Economics (PIDE),
Islamabad.

Head Department of Environmental Economics:

____

Dr. Rehana Siddiqui
Pakistan Institute of
Development Economics (PIDE),
Islamabad.

Dedicated to My Beloved Parents

Certificate of Originality

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Signature:

Author Name: Zeeshan Mustafa

Date: January, 2015

Abstract

Climate change is one of the biggest confronting challenges to mankind. The impacts of the climate change have affected agriculture crop sector specifically. Many researchers attempted to compute the effect of climate change mainly on food crops since decades. Although, the estimation technique and construction of the variables were under the great debate and various researchers pointed out problems present in literatures. Therefore, serious attempts are required to estimate the climatic effects on other crop(s) with superior estimation technique and concrete method of variables construction based on strong theoretical background. This study estimated yield and acreage responsiveness of sugarcane crop to climate change in major sugarcane producing districts of Pakistan using fixed effect model and Arellano Bond GMM estimation technique. The results showed that sugarcane yield is more sensitive to precipitation at different phenological stages including germination, tillering and grand growth stages than temperature whereas the effect of agricultural production technology (0.087) was positive. Moreover, severe climatic incidents like drought showed negative impact (-0.024) on the crop yield. Therefore, abrupt changes in climatic condition adversely affected the crop production in Pakistan. Price and non-price factors were important determinants for sugarcane acreage allocation. The result showed that own-price of sugarcane had significant positive impact (0.149) on area allocation. However, the relative prices of substitute crops viz. cotton (-0.027), maize (-0.003) and wheat (-0.22) had negative impact on area allocation. It could be crucial to invest in Research and Development (R&D) for developing improved drought tolerant sugarcane varieties to minimize the risk of yield losses due to changes in climatic conditions in Pakistan.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background

Temperature is rising consistently due to accumulation of greenhouse gases (GHGs) in Earth's atmosphere. The excessive use of resources from human beings speeded up the process of global warming and its associated anomalies. Human induced warming increased rates of rainfall and patterns, vulnerability of semi-arid regions to drought and intensity of the temperature. The effect of variability would be critically dependent on the extent of the warming and occurrence rate (National Research Council, 2001).

The outdoor production processes involved in agriculture--most climate-sensitive sectors that dependent on certain levels of temperature and precipitation among other climatic factors. Climate change has adversely affected the economic performance of the sector worldwide. The share of the agriculture in high income countries is less than two percent of their gross domestic product (GDP) whereas nearly three percent for the world as a whole[1.]. In case of low income countries, it is more important amounting to almost one-fourth of GDP. Agriculture sector encompasses of the products which are an absolute necessity of life that have no substitutes[2] virtually. Agriculture provides both sources and sinks of greenhouse gases (GHGs). GHGs are emits due to intensive tilling and fertilization during food supply processes. The world population faces challenges due to increased agricultural production with enhanced risks of GHGs emissions and degradation of

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[1] World Bank data on agricultural value added as a share of GDP in 2008, http://data.worldbank.org.

[2] In economic terms, the fact that food is a necessity means that it has a very low price elasticity of demand, Implying that it has a very large consumer surplus.

environment. According to the estimates, agricultural activities are responsible for 20 percent greenhouse effect (Cole et al., 1997). In order to maintain global food security, we must consider the issue of climate change because agriculture is among most susceptible sectors. Most of the developing economies mainly rely on their agriculture sector— the main contributor in GDP (Mertz et al., 2009).

The prevailing climatic conditions are important causes of year-to-year variability in crop production in high yield[3] and technology environment. The yields of others crop(s) and geographic limits may be transformed by different factors like soil moisture changes, cloud cover and CO_2 concentrations increase. Crop yield shows both positive and negative response due to rising CO_2 levels. The low rainfall and increasing temperature could decline soil moisture in various areas, reduction in available water for irrigation and harming crop growth in arid regions of the numerous regions (Aydinalp and Cresser, 2008; Fischer et al., 2002).

The serious concerns have been arises due to climate change and their impacts on agriculture. Research shows that climate change effects would not be uniform across the globe within different segments of the societies. Agricultural supplies and relative prices would also be affected by climate change. This may result in a resource re-allocation between sub-sectors of agricultural, modifying the configuration of the economies of several countries and pattern of international trade (Deke et al., 2001). Many studies showed that, in marginal areas the implications of climate change are a poverty threat in reduction and efforts for sustainable development. Nevertheless, the relationship between climate change and agriculture is complex, because this encompasses climatic, environmental and socio-economic responses (Quiroga and Iglesias, 2008). Climate

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[3] Output per acre

change is altering crop yield levels and these effects vary across various types of crops. Studies showed that increase and variability in rainfall and temperature have been increasing yield level in case of sorghum while vice versa in case of corn. Liu et al., (2004) suggested that both higher temperature and more precipitation would have an overall positive impact on China's agriculture under most climate change scenarios. However, there is a large seasonal variability across the regions. The effect of autumn season is positive while spring effect is negative.

In agrarian economies like Pakistan, the agricultural production level primarily depends on, inter alia, the area under cultivation. The decision related to allocation of the area under crop by the farmers largely depends on previous and future year prices of the crop concerned among other things. Thus, the future prices trend confirmed that the prices will go up from previous year prices. As a result, farmers have decided to allocate more area under cultivation in order to reap benefits of the higher prices. The responsiveness of the area under food and nonfood crops to the changes in the lag year prices of the crops disturbed is incredibly crucial to comprehend the behavior of the farmers (Aruna and Upender, 2012a).

Abrupt price changes and climate could have robust changes in the farmland allocation among alternative crops. The crop price swing has led to questions including how cropping area will change and the subsequent impact on other sectors of the economy. Moreover, questions are arising about how climatic change may affect the types of crops being grown and thus local prices (Smithers and Smit, 1997). Farmers are adopting different adaptation strategies to cope with climate change effects including changes in the average and variance of weather conditions (Bryant et al., 2000). Crop prices responded to exogenous shocks in acreage supply. There were two types of shocks including crop's own acreage and shock and shocks to total cropland reported in literature. A negative shock in own acreage leaded to a spike in crop prices [in USA, for both soybeans and corn]. The reduction in corn area of one million acres resulted in a corn price increase of \$0.04 to \$0.07 per bushel. Price of soybeans increased when reduction in acres happened (Almirall et al., 2012a).

Sangwan, (1985a) reported that sugarcane crop showed positive relationship with lagged year crop prices and yield. He also tried to quantify the impact of climatic variable (rainfall) on sugarcane acreage but didn't able to report in the results due to data estimation problems. Actually, his studied covers the complete cropping patterns in Haryana state (India). Therefore, due to methodological problems and estimation biased, sugarcane crop acreage response to rainfall didn't estimate accurately. Weersink et al., (2010a) confirmed that climatic variables have significant impact on area allocation. They revealed that a longer growing season[4] will increase planted area of crops including corn, soybean and winter wheat. Even without changes in crop prices, farmers are using crop area allocation as an adaptation strategy to climate change.

Pakistan is an agro-based economy, in which over 43.7 percent of its population earn their livelihood from agriculture. The share of agriculture sector is 21 percent to its GDP (Government of Pakistan, 2014a). Vagaries of climate change would affect the Indus Basin, which is the cradle of Pakistan's agriculture. The most parts of Pakistan are arid to semi-arid with significant spatial and temporal variations in climatic parameters based on their climatology. The studies have forecasted that temperature would rise by 3°C by 2040 and up to 5-6°C by the end of the century in Pakistan (IUCN, 2009a). In Pakistan, about 59 percent annual rainfalls are due to monsoon rains called a dominant hydro-meteorological resource for Greater Himalayan region. The winter precipitation is mostly received in the form of snow and ice. Above 35°N, snow melting is main

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[4] length of the growing season measured in days, starting when the mean daily temperature is greater than or equal to 5°C for five consecutive days beginning March 1 to the end of October

source to keep the rivers perennial throughout the year (Farooqi et al., 2005). A drastic reduction in rate of monsoon rains and increase in frequency of droughts and floods are predicted for the whole of South Asia. The issue of climate change is altering the crop rotation and cropping patterns resulting in significant decline in crop production including wheat, rice, cotton, and sugarcane. Under the climate change scenario, production of high delta water-consuming crop like sugarcane may no longer be feasible. In Pakistan, sugar prices have more than doubled in 2009, creating social unrest and political embarrassment (IUCN, 2009b).

Sugarcane is one of the important crops that provides about 75 percent of sugar produced in the world for human consumption (De Souza et al., 2008). The sprouting and emergence of sugarcane negatively affect due to increase in temperature (Rasheed et al., 2011) in turn affecting plant population and reducing crop yield. In addition, as the temperatures increase [above 32°C] results in short internodes, increased number of nodes, higher stalk fiber and lower sucrose contents (Bonnett et al., 2006a). Furthermore, Clowes and Breakwell, (1998) found that the yield of cane and sucrose contents are adversely affected due to increase in temperatures (especially at night) through inducing more flowering of sugarcane thus ceasing growth of leaves and internodes.

The climate change related factors associated with crop production include drought, flooding, salt stress and extreme temperatures. The growing seasons are modifying due to extreme changes in rainfall patterns and a rise in temperature which could subsequently reduce the crop productivity. Few empirical studies have been done in this regard to estimate the impact of climate change and supply response behavior of the sugarcane crop in Pakistan whereas existing literature mainly covers grain crops including (Mushtaq and Dawson, 2002a). Moreover, the literature shows that there is a dearth of research in the developing economies related to climate change and acreage response. Few studies conducted in this regard to address the issue at disaggregate (district, county or agro-ecological zones) level and examine the impact at important phenological stages of the sugarcane crop.

1.2 Research Gap

The objective of agricultural policy inter alia, is for fair incomes of the farmers, low prices of food for urban consumers, raw materials at cheap rate to the manufacturing sector, and increasing exports in Pakistan. The prices of major agricultural crops are often set lower as compared to the world prices through support price policy instrument. The previous studies differ in their scope, data they use and in their econometric techniques. They also differ in the way they measure the climate variables, in the level of dis-aggregation of data and the size of the panel data included (Huang and Khanna, 2010a).

Pakistan's major crops such as wheat, rice, maize, cotton and sugarcane account for 25.6 percent of the value added in agriculture sector and 5.4 percent to GDP. Sugarcane occupies an important position in national economy feeding a sizeable domestic sugar industry and providing raw materials to clip board, paper and ethanol manufacturing. Its share in value added agriculture and GDP is 3.4 percent and 0.7 percent respectively while foreign export earnings from sugar export is US$ 236.8 million (Government of Pakistan, 2014b). Pakistan is the 5th largest sugarcane producers in the world. Despite its small contribution towards agricultural value added in the economy, sugarcane remained important due to its linkages with other sectors of the economy and political sensitivity. In the past, high prices of sugar have resulted in severe political crises in the country. However, the effect of climate change on productivity of sugarcane in Pakistan has been rarely analyzed. The major focus of the earlier studies [except few including (Siddiqui et al., 2012a)] regarding the topic has mainly been on the cereal crops.

This study would explore the impact of climate change on production of sugarcane crop while controlling for technological changes [through incorporating investment in research and development (R & D) of sugarcane] and other important factors. Most of studies on impact of climate change on crop(s) cover few districts and/or one particular province while this study would cover all the major sugarcane producing districts of Pakistan.

Construction of the climatic variables are one of the important factor that significantly affect the outcomes of any empirical study. Previous studies, constructed climatic variables (including temperature and precipitation) on the basis of averaging different seasonal values. Although, climatic variables effect differently and their affects depends upon particular crop behavior. Moreover, previous studies intentionally and/or unintentionally ignore the principal definition of climate change for the construction of variables [including (Hanif et al., 2010a)].

Therefore, this study carefully consider the pre-requisite of studying climate change impacts. Climatic variables (temperature and precipitation) were constructed at phenological stages of sugarcane crop using 20 years moving averages values. In addition, sever climatic incidence like drought and weather shocks in long term norms were also considered to quantify the effect of climate change in the presence of other important variables like fertilizer (share of sugarcane crop in each district in given year), irrigation (no of tube wells) etc. Technology is one of the important factor in the agriculture production system and most of the researcher(s) used time trend (proxy) to capture the effect of technology on crop production. Whereas, literature suggested that using time trend in estimating response of crop (production and acreage allocation) gave biased results. Time trend is highly correlated with carbon dioxide (CO_2). Therefore, time trend gave us also the CO_2 fertilization effect (Zepeda, 2001a). In addition, agricultural research and development (R&D) investment were used to get the reliable estimates.

1.3 Significance of Study

This study differs from others in the following ways. We intend to estimate responsiveness of both yield and sugarcane acreage (in Pakistan) to climatic factors and socioeconomic variables using disaggregated data at the district level. While controlling for other important variables, the study have analyzed the effect of climate change (long run changes in temperature and precipitation) as well as weather shocks (deviation of temperature and precipitation from long run norms) on sugarcane yield and acreage allocation. The study has also capture the effect of drought and R&D expenditure on sugarcane crop in Pakistan.

1.4 Objectives

The main goal of the study is to explore the relationship between climate change and production of sugarcane crop in Pakistan. The more specific objectives of the study are as follows

1. To quantify the impacts of climate change on yield of sugarcane.
2. To analyze the responsiveness of sugarcane acreage to climate change
3. To suggest policy recommendation for sustained growth of sugarcane production based on empirical findings

1.5 Hypothesis

Keeping the above mentioned objectives in view and after thoroughly studying the past theoretical and empirical research, we have formulated the following hypotheses:

Hypothesis I

H_0: overtime variations in temperature have no effect on yield of sugarcane crop.

H_1: overtime variations in temperature have an effect on yield of sugarcane crop.

Hypothesis II

H_0: overtime variations in precipitation have no effect on yield of sugarcane crop.

H_1: overtime variations in precipitation would have an effect on yield of sugarcane crop.

Hypothesis III

H_0: overtime variations in temperature have no effect on allocation of acreage to sugarcane crop.

H_1: overtime variations in temperature and precipitation effect allocation of acreage to sugarcane crop.

1.6 Organization of the Study

To address the above given objectives, the study proceeds in the following manner. Chapter 2 review of literature --highlighted the important studies on climate change and its impacts on crop yield and acreage response in presence with other explanatory variables; Chapter 3 explains the methodological framework for explaining the impact of climate change on crop yield and acreage model. Chapter 4 explains the construction of the variables and discusses econometric models to be estimated. Chapter 5 deals with estimation and discussion of the results, Chapter 6 gives conclusions and suggests some policy recommendations.

Chapter 2

Review of Literature

The unchecked development of greenhouse gases' emissions increases the temperature of the earth. The consequences include melting of glaciers, more precipitation and extreme weather events, and shifting of seasons. The overall expected impacts of climate change on agriculture are negative including threatening global food security. However, there would be gains in some regions of the world in some crops. Populations in the developing world (which are already vulnerable and food insecure) are likely to be the most seriously affected (Nelson et al., 2009).

Recent research findings depicted an ominous picture of climatic effects on agriculture as compared to the relative optimism of research from the 1990s. The earlier research findings are continuously using in economic models and climate policy that create unprovoked complacency to develop climate policy on priority basis. These studies concluded that the initial stages of climate change would bring net benefits to global agriculture (Ackerman and Stanton, 2012a).

Climate change will have a significant impact on agricultural commodities, viz. production and their productivity which leads to both food supply and food security concerns in least developed countries (LDCs). Climate change is happening and already having a drastic impact on climatic variability, global temperatures and sea level without any doubt. There will be a significant impact of climate change on agriculture that links between climate (temperature and precipitation in particular) and productivity. These effects are likely to have greatest effect in the LDCs of the tropical zones where productivity would decrease. A significant occurrence of extreme events, heat stress, droughts and floods, would increasingly have negative impacts on crop yields. The ability of farmers and rural societies to adapt to these changes is vital for maintaining an adequate global food supply. Although, demand is likely to increase, due to rising global population size primarily, climate change would challenge agricultural production and food security. As projected, agriculture output in LDCs may decline by 20 percent due to climate change and yields could decrease by 15 percent on average by 2080 (Masters et al., 2010). This section is divided into two part based on available literature; firstly, climate change, drought and yield response studies were discussed and secondly, few important literature were reviewed that highlighted the acreage response to climate change and price

2.1 Climate Change, Drought and Yield Response

Chen, et al., (2004) examined the extrapolated potential effects of climate change on corn, cotton, wheat, soybean and sorghum crop yield under projected climate change. In specific, maximum likelihood panel data estimates of the impacts of climate on year-to-year yield variability were constructed for the major U.S. agricultural crops. The results highlighted the crop specific variations in the impacts of climate on yield levels and variability. For corn, precipitation and temperature results were reported to have opposite effects on yield levels and variability. More rainfall stimulates corn yield levels to rise, while decreasing yield variance (variability). Temperature has the reverse effects on corn yield levels and variance. For sorghum the effects go in the same direction, with higher temperatures declining yields but also reducing variability. More rainfall increases sorghum yields but also increases variability.

Batima et al., (2005) calculated changes in temperature and precipitation with seasonal and spatial variability as well as some climate extremes indices for Mongolia. The results showed that annual mean surface air temperature in Mongolia has risen [1.66°C], warming faster in winter than in summer, during the 1940-2001 period. High mountainous areas and their valleys were more affected from climate change except the Gobi desert. Extreme indices (heat wave duration, cold wave duration, maximum number of consecutive dry days as well as maximum number of wet days) have been calculated with the STARDEX extreme index software. There had been a statistically negligible decline in annual precipitation reported. Spatially, annual mean precipitation has been declining in central Mongolia but increasing in both the eastern and western regions of the country. Seasonally, both winter and spring precipitation have decreased, while summer and autumn have registered no changes.

Seo et al., (2005) used the Ricardian method to measure impact of climate change on Sri Lankan crops including paddy, coconut, rubber and tea crops. They studied the limited and greater range impact of temperature as well as precipitation. The result of Atmosphere-Ocean General Circulation Models (AOGCM) scenarios showed that the increased rainfall impacts were forecasted to be beneficial for country as a whole in all five scenarios (CSIRO,PCM, CCSR, CGCM and HAD3), nevertheless temperature increases were predicted to be harmful. The result suggested that depending on the actual climate change scenario, the climate change damages could be large in tropical developing countries.

Greenland, (2005) analyzed the role of climate erraticism on annual yield of sugarcane in Louisiana. He used the climate database and yield data for the period of 1963 to 2002. The climatic variable constructed from daily and monthly values of maximum and minimum temperature. In addition, daily and monthly total precipitation for six cooperative weather-reporting stations (representative of the area of sugarcane production) were also included. The fact that a climate variability exists was verified by comparing mean values of the climate variables corresponding to the upper and lower third of adjusted yield values. Most of these mean-value variances showed an instinctively acceptable difference between the high- and low-yield years. In addition, the constant high water table and soil water availability with higher precipitation totals have a negative effect on the yields. Past trends in the values of climatic variables and general projections of future climate suggested that, future levels of sugarcane yield would rise in Louisiana (with respect to the climatic environment).

Deressa, et al., (2005) examined the impact of climate change in South African sugarcane production under irrigation and dryland conditions. They used a Ricardian model and time series data for the period 1977 to 1998 pooled over 11 districts. The results showed that climate change had a significant non-linear impact on net revenue per hectare of sugarcane. Also, a higher sensitivity to future increases in temperature was predicted than the precipitation. Irrigation did not provide an effective option for mitigating climate change damages for sugarcane production. Results of a critical damage point analysis combined with agronomic knowledge about optimal climatic conditions for sugarcane production indicated that sugarcane production in the study area would be less sensitive to increases in rainfall levels than temperature.

Gbetibouo and Hassan, (2005a) used a Ricardian model to measure the climate change impacts on South Africa's field crops and analyzed likely imminent effects of further changes in the climate. A regression of farm net revenue on climatic variables, soil characteristics and other socioeconomic variables was estimated to internment farmer-adapted responses to climate variations. The analysis was comprises on agricultural data for seven field crops (maize, wheat, sorghum, sugarcane, groundnut, sunflower and soybean) and climate data across 300 districts. Results indicated that production of field crops was sensitive to marginal changes in temperature as compared to changes in precipitation. Temperature and rainfal shows positive and negative effects on net revenue, respectively.

Hussain et al., (2005) estimated the climate variability in the mountain areas of Pakistan covering winter dominated high mountain region and monsoon dominated sub-mountain region. Winter season temperatures have increased in both studied areas during the period of 30 years (1971-2000). Relatively higher increase in maximum winter temperatures was observed, whereas minimum temperatures during winter showed a slight decline. These results suggested that days have become warmer whereas nights have become cooler during the winter season in the high mountain areas. Maximum temperature in monsoon season have also increased in both the regions. More interestingly, maximum temperatures in the transitional periods “October-November” and “April-May” particularly in the high-mountain areas were at a rising trend. They concluded that the increasing trends in temperature in the high mountain areas may have some positive impact on crop area and yields as well as enhance the overall de-glaciations process in the country.

Binbol et al., (2006) investigated the effect of climate on growth and yield of sugarcane at the Savannah Sugar Company in Numan, Nigeria. The relationship between sugarcane yield and climatic factors at different phenological stages of the crops were examined using stepwise regression. Two climatic variables were found as the critical factors effecting crop yield: pan evaporation at the ‘boom’ (or ‘grand growth’) stage, and minimum temperature at germination stage. More than 68 percent variation in the yield of sugarcane was due to these factors. Combined effects of the different climatic variables contributed significantly to the variation in yield of sugarcane.

Tao et al., (2006) used crop and climate data from representative stations across China for the period 1981–2000. They investigated the trends of climatic variables and the the effect of climate change on the development and production of the staple crops—rice, wheat and maize. They observed substantial warming trends at most of the examined stations, and the variations in temperature have shifted crop phenology and affected crop yields during the two decades. The observed climate change patterns and their impacts were diverse both spatially and temporally. The sensitivity of crop responses to temperature change was affected by other factors such as changes in other climate parameters (e.g. precipitation), and management practices, suggesting a potential role of management for adaptation.

Hussain and Mudasser, (2007) used ordinary least square method to evaluate the climate change impacts on wheat yield in Chitral and Swat districts of Khyber Pakhtunkhwa province (formerly North West Frontier Province) of Pakistan. Results reveals that increase in temperature would result in positive impact on wheat yield in Chitral district (located on high altitude) and a negative effect in Swat district (located on low altitude).

Huang and Khanna, (2010b) conducted an econometric analysis of the factors influencing U.S. crop yields and allocated acreage using U.S. county level data from 1977 to 2007. They used instrumental variable regression methods to control endogeneity of prices and county specific fixed effects for unobserved location specific effects. They found that corn, soybean and wheat yields all respond positively to their own prices and that corn and wheat yields respond negatively to fertilizer prices. Substituted crops acreage[5] have a positive impact on corn yield but no significant impact on soybean yield. Moreover, they found that climate variables (temperature and precipitation) have a significant impact on the yields for all the three crops. The results showed that increase in temperature lead to reduced crop yields while more precipitation would just enhance corn and soybean yields.

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[5] defined as the minimum of the increase in acreage of a crop (relative to previous year) and the decrease in aggregate acreage of all other crops

Kim and Pang, (2009) investigated the association between rice yield and weather variables in Korea by a stochastic production function. The results revealed that rice yield was positively related to temperature and negatively associated with precipitation. Moreover, rice yield variations were positively respond to both temperature and precipitation (risk increasing inputs). The larger rice yield variability due to weather fluctuations results in production losses and price volatility. Larger market risk would be anticipated in the future since both temperature and precipitation are predicted to increase.

Janjua et al., (2010) employed the vector auto-regression model in order to check the impact of climate change on wheat production in Pakistan. The results revealed that there were no significant negative impact of climate change on wheat production. The results confirmed that forecasted impact of crop area and climatic variables (temperature and precipitation) caused 30 and 34 percent variation in wheat production, respectively.

Ahmed and Schmitz, (2011a) used fixed effect panel data technique to evaluate the effect of climate change on agricultural productivity in Pakistan`s four provinces, Punjab, Sindh, Balochistan and Khyber Pakhtunkhwa (formerly North West Frontier Province), calculated as weighted food crop yields[6] per hectare, for wheat along with (rice and maize). For wheat, they considered RABI (Nov-Apr) growing season and including a measure for drought to capture the occurrence of extreme events, aggravated through climate change.The results confirmed that a one degree increase in temperature reduced food crop yields by forty four kilos per hectare. The incidence of climatic extremes has been modeled using a measure for drought

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[6] Ratio of weighted sum of all crop production to their respective area

constructed via precipitation deviations from long term normals. As expected, this variable has a negative significant effect on food crop yields.

Ashfaq et al., (2011a) investigated wheat productivity in mixed zone of Punjab province of Pakistan using time series data from 1980-81 to 2008-09. The impact of climate change on wheat productivity was analyzed controlling for some economic variables. The results showed that one degree centigrade increase in mean minimum temperature at sowing stage would increase wheat productivity by 146.57 kilogram per hectare. At vegetative growth stage, the increase in mean maximum temperature would reduce productivity, although non-significant, by speeding up vegetative growth and reducing grain development period. On maturity stage, the productivity gain would be 136.63 kilograms per hectare as result of one degree centigrade increase in mean maximum temperature while effect of rainfall[7] during wheat growing season would enhance wheat yield by 275.77 kilograms per hectare. They concluded that the climate change was major determinant of wheat productivity at each stage of wheat growth.

Cai et al., (2012) investigated the spatially varying relationship between climatic variables (weather) and corn yields with the help of geographically weighted panel regression analysis. A balanced panel data of 958 U.S. corn production counties for the period 2002-2006 was used. The results found that the relationship between climatic variables and corn yield has large spatial variability. In specific, temperature tends to have negative marginal effects on corn yield in warmer regions, and positive effects in cooler regions.

Lee and Nadolnyak, (2012) developed the pooled cross-section farm profit model to estimate the climate change effects on U.S. agriculture. The data were mainly based on the annual agricultural

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[7] Binary variable 1 if rainfall is greater than 70 mm during wheat growing season and 0 otherwise

resource management survey from United States Department of Agriculture (USDA) for the time period between 2000 and 2009 in 48 contiguous States. The growing season drought indices - Palmer Drought Severity Index (PDSI) and Crop Moisture Index (CMI)[8] were used in the analysis and both indices depicted a negative relationship with temperature. The results showed that one unit increase in PDSI leads to 5.5 percent, 4 percent and 5 percent increase in farm profits for all farm, crop farms and livestock farms, respectively. Similarly, the result of the CMI indicated that one unit increase in the index would induced 13.9 percent, 9 percent and 14 percent increase in the farm profit of all farm, crop production farms and livestock farms, respectively. They concluded that drought indices (PDSI and CMI) were better variables to be used for estimating the impact of weather on farm profits whereas temperature, precipitation, and growing degree-days are typical used weather variables in literatures.

Mahmood et al., (2012a) found that the pattern of temperature and precipitation were changing due to global warming and affecting rice productivity in the rice-wheat cropping system of the Punjab. Province level aggregated time series data were used to estimate Cobb Douglas type production function with rice yield as dependent variable. There were several climatic variables used as explanatory variables including mean minimum and mean maximum temperature for July-August and September-October respectively. However, mean rainfall for July-August and September-October were used as other climatic variables, respectively. There were different scenarios were developed to estimate the effect of temperature and precipitation on rice yield. The results of these scenarios showed that overall increase in temperature by 1.5°C and 3°C would increase rice yield by 2.09 percent and 4.33 percent, respectively [compared to the base year

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[8] Higher indices value indicate favorable agriculture production environment

regression estimates]. However, an increase in precipitation by 5 percent and 15 percent[9] during September-October could adversely affect rice productivity by 5.71 percent and 15.26 percent, respectively.

Sarker et al., (2012) investigated the association between yield of three major rice growing seasons (Aus, Aman and Boro) and climate variables (maximum temperature, minimum temperature and rainfall) for Bangladesh. They used time series data for the 1972–2009 period at an aggregate level to measure the relationship between climate variables and rice yield using both the ordinary least squares and median (quantile) regression methods. The results of the study suggested that climate variables had noteworthy effects on rice yields, albeit these effects vary among three rice growing seasons.

Siddiqui et al., (2012b) studied the impact of climate change on four major crops including wheat, rice, cotton and sugarcane production in seven districts of Pakistani Punjab at different phenological stages of each crop. Estimation employing fixed effect model was done using the panel data on climatic variable (temperature and precipitation) regarding phenological stages of each crop. Quadratric form of temperature and precipitation were also used to account for the possible non-linear impact of climatic variables. District dummies were aslo incorporated in the regression to capture the effect of district specific characteristics. The result showed that district level attribute play important role in crop production (soil characteristic). The findings showed that immediate (short run) as well as forecasted (long run) effects of climatic variables (temperature and precipitation) were positive for wheat vice versa for rice, cotton and sugarcane.

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[9] Precipitation scenarios

Witter, (2012) studied potential impact of climate change on sugarcane and yam in Jamaica's five main climatic regions. The explanatory variables included three types of variables, economic variables (basically prices), climatic variables (temperature, rainfall) and geophysical variables (soil type, soil erosion, salinity, etc.). According to the IPCC Special Report on Emissions Scenarios (SRES) under A1 and B2 scenarios[10], results exhibited that for sugarcane production to be maximized, rain in the growing season (April to July) must be higher than or equal to the optimum 189.93 mm per month. Although, in the ripening season (August to November) rain must be less than or equal to the optimum 195.76 mm per month. Furthermore, in the reaping season (December to March), rain of at most 101.77 mm per month is optimal. Deviation around the mean temperature has a negative impact on sugarcane yield. Generally, increases in temperature above the average temperature (29.43°C) have a negative impact on sugarcane yield, while decreases below the average increases the yield.

Chen, et al., (2013) used a unique county-level panel on crop yields and daily weather dataset over the past decade. They estimated the impact of climate change on corn and soybean yields in China. Their results suggested that existence of nonlinear and asymmetric relationships between corn and soybean yields and climate variables. They found that extreme high temperatures were always harmful for crop growth. Moreover, the rapid expansion of corn and soybean acreages at both intensive- and extensive margins had detrimental effects on corn and soybean yields. Using estimated coefficients, they calculated that change in climatic conditions over the study period has led to an economic loss of $220 million in 2009 alone in China's corn and soybean sectors. Corn

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[10] A1 scenario describes as future world of very rapid economic growth and global population whereas B2 describes as convergent world with the same global population that peaks in mid-century and declines thereafter

yields in China were predicted to decrease by 2-5 percent under the slowest warming scenario and by 5-15 percent under the fastest warming scenario by the end of the century. The reductions in soybean yields were found to be more obvious, about 5-10 percent and 8-22 percent, respectively.

2.2 Climate Change, Price and Acreage Response

There is a prevailing perception that farmers in less developed countries react gradually to economic incentives such as price and income. Several studies available for India at the crop level confirmed that the supply response is less elastic (Askari and Cummings, 1977a). The reasons behind this poor response due to diverse factors such as constraints on irrigation and infrastructure to a lack of complementary agricultural policies. The response of the farmers estimated by various researchers are vary due to some conceptual problems to identify the precise form of climatic variable and prices as well as the estimation technique under the conceptual methodological framework.

There are few scholars that worked with panel data in supply response analysis. Kumar and Rosegrant, (1997) and Kanwar, (2004a) are the few who used pooled cross-section-time-series data, especially across regions of India. There is a dearth of studies which investigate the response of sugarcane crop particularly with larger panel data.

Chavas et al., (1983a) analyzed the role of futures price, cash price, and government programs in acreage response for U.S. corn and soybeans. The result showed that the government corn support price program played a foremost role in corn and soybean production decisions. Also, the results indicated that expected prices were not good proxies for projected future cash prices in the existence of government programs. They raised questions about the informational effectiveness of futures prices when government interferes in the market place.

Sangwan, (1985b) used Nerlovian model to calculate the acreage response to prices for complete cropping pattern[11] cultivated crops in Haryana state, India. The result reveals that acreage of rice, barley, gram and rapeseed have significant positive response to rainfall while American cotton has significant negative response. Cash crops including wheat, sugarcane and American cotton have significant positive response to own prices. Moreover, wheat acreage has significant negative response to price risk. Furthermore, the study confirmed the earlier hypothesis that cash crops were more elastic to price movements than food crops.

Burt and Worthington, (1988) reported that wheat acreage response was more complicated as compared to previous studies. They used distributed lag response, which is believed to originate from the effect of summer fallow in crop rotations in the Great Plains. The result showed that acreage response elasticity estimated was 1.3 [Great Plains] at average price and for the aggregate U.S. it was 1.5. For USA, the proportion of long-run response experienced over the first five years were 0.24, 0.44, 0.70, 0.95, and 0.99 from an increment to price respectively.

Alemu et al., (2003) used error-correction model to quantify the responsiveness incentives of producers of grain crops (wheat and maize) and forage crops (teff and sorghum). The result confirmed that there was a positive effect of own price on planned supply of these crops while effect of substitute crop prices was negative. Similarly, negative relationship exists with various structural breaks related to policy changes as well as the manifestation of natural calamities. They found noteworthy long-run price elasticities for studied crops and insignificant short-run price elasticities for all crops except maize. The elasticities of the crop may vary due to farmer's perception about certain price changes whether these changes were permanent and temporary.

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[11] Rice, Jowar, Bajra, Maize, Wheat, Barley, Gram, Rapeseed & Mustard seed, Groundnut, Cotton (American and Desi), Sugarcane and Potato

They concluded that farmers were responsive to incentive changes. Therefore efforts, which directly or indirectly tax agriculture with the conviction that the sector is non-responsive to incentives, would harm its growth and its role to growth in other sectors of the economy.

Mushtaq and Dawson, (2002b) highlighted and analyzed the supply response of wheat, cotton, sugarcane and rice in Pakistan using co-integration analysis and impulse response analysis using 1960-96 annual data. Results indicated that long run own price acreage elasticity for sugarcane was 5.01 while for wheat and cotton was 0.93 and 0.30, respectively Moreover, the wheat supply was found to be inelastic both in the short- and long-run while cotton supply was elastic in the long-run.

Abrar et al., (2004) used farm-level survey data from Ethiopia and estimated a quadratic restricted profit function to measure the supply response of smallholder farmers. Response of peasant farmers was positive and significant to price incentives in the more marketable central and southern zones. Farmers in the Northern zone were least commercial as well as reactive to prices, and in fact the model based on profit maximization didn’t adequately capture their behavior. In over-all, non-price factors, particularly rainfall and market access, were more important than prices in affecting production, and which factors were most important varies depending on the crop and region in question..

Talb and Begawy, (2008) highlighted the responsiveness of wheat, clover, summer rice and summer maize producers using a vector error correction model. It was revealed that planned supply of these crops was positively affected by own producer price (except clover). While, prices of substituted crops effect negatively and structural breaks related to changes in the economic systems. They reported that long and short run price elasticities of wheat and summer maize were significant and positive among all other studied crop. Long-run elasticities ranged from 0.072 to 0.140, which was very low due to severity of structural constraints that Egyptian farmers were facing. The results may suggested that it takes time before farmers obtained information about price changes due to infrastructural barriers because the farmers react to price changes only when they were assured that the changes were permanent.

Shaikh and Shah, (2008) used Nerlovian model to quantify the effect of price on rice acreage of Pakistani rice growers during period 1961-2005. The result showed that rice acreage has significant positive response to rice price. Moreover, the long run and short run acreage elasticity of rice crop were 0.10 and 0.12, respectively.

Vitale et al., (2009) used data set of 82 farmers over 14 years, from 1994 through 2007, to estimate Nerlovian supply response model for cotton, maize, sorghum, and millet in long-term rotation. Two stage least squares equations were used to estimate the supply response. The results showed that the cotton producers have reacted to prices in a relatively inelastic manner, with supply elasticities only about one-half of those estimated for producers in developed countries. They emphasized policy reforms that could help producers respond more easily to prices changes as well as to raise average productivity levels.

Molua, (2010a) estimated supply response function for rice in Cameroon. The result confirmed that lagged acreage and weather in terms of rainfall have significant positive effect on current year acreage. Moreover, the positive coefficient of lagged rice price ratio in the acreage equation showed direct relationship with rice acreage, and indicated that price influenced area under cultivation. It was perceived that the rice area grown may increase 1.35 percent for a ten percent increase in relative world price to producer price. A ten percent increase in relative price of substitute maize crop accounted for 1.17 percent decline in rice area.

Weersink et al., (2010b) used seemingly unrelated regression to estimate the impacts of weather on the distribution of yield as well as its subsequent effect on the acreage allocation decisions of agriculture crop farmers in Ontario (Canada). The average and variance of yield were estimated for corn, soybeans, and winter wheat for eight counties for 26 year period. The results explored that both future price and yield are important in the area allocation decisions. These results were different from previous research, which has focused almost exclusively on the effect of prices and its impact on crop profitability. The yield and area elasticities to prices were estimated. The yield elasticity was slightly higher as compared to area to prices. Therefore, area allocation is the important factor based on farmers decisions for yield. A longer growing season will increase the area planted to all three crops considered in their research.

Bhatti et al., (2011) developed another specifications of model of supply response of Pakistani wheat growers from 1961-2008 dataset and their economic implications were considered in terms of the existences and nature of production lags. The examined that there were lags due primarily to the difficulties and cost of rapid adjustment rather than because of the time required to revise expectations. The statistical results presented that lagged price and production of wheat have significant positive effect on current year crop acreage whereas lagged cotton production effect was insignificant. Acreage response of wheat to own price was 0.08 and 0.11 in short run and long run, respectively.

Yaseen et al., (2011) used 42 years (1966-2008) dataset to develop two classic trans-log models for approximating the reactions of areas of wheat, cotton, rice, maize and sugarcane crop specifically to changes in their gross product per hectare. They found that the production of cash crops in developing countries is a vital factor vis-à-vis farmers, population growth and economic development. The own and cross gross product elasticities for each crop were calculated and compared to the data existing in literature. The result showed that the major crops were weakly responsive to gross product as compared to minor crops. Moreover, Pakistani producers have responded weakly to gross product as compared to Indian producers. Average productivity levels depend on policy reforms, so that producers respond more easily to price changes.

Almirall et al., (2012b) estimated the own- and cross-price elasticities of five major crops including wheat, cotton, rice, sugarcane and maize in Pakistan. Zellner's Seemingly Unrelated Regression Method (SUR) was used to estimate the supply response for each crop. The assumption of homogeneity of degree zero of the supply response function allowed the normalization of crops prices with respect to fertilizer price in each equation. The autoregressive integrated moving average model was applied to estimate the expected normalized price series of each crop. The expected normalized prices were used to approximate the supply response functions from which short- and long-run own-, cross- and fertilizer-price elasticities were estimated. Farmers had adjusted their resources among different crops in response of output and changes in fertilizer prices. Short-run own-price and fertilizer price elasticities of all the five major crops were noteworthy, at least at the 20 percent significance level. The price support has little prospective to increase overall agricultural productivity. The food crops like wheat and maize have low own-price elasticities, though price support in these crops will have a little effect on the production of other crops (because low cross-price elasticities with respect to food-crop prices). On the other hand, cash crops like cotton and rice have relatively high own-price elasticities, but price changes of these crops have very strong negative effect on the production of other crops (because of robust cross-price elasticities with respect to cash-crop prices).

Maji et al., (2012) examined the effect of various changes in price and non-price factors on supply response of farmers of Murshidabad district of West Bengal. They confirmed that previous year area and price exert positive and significant influence on acreage response for all crops whereas lagged price was the single most important factor responsible for yield response. Price as an important tool for achieving increased production with low magnitude of short run price elasticity of acreage and yield of all crops may have a limited role to play whereas higher value of long run price elasticity of both acreage and yield suggest that price may exert significant influence on farmers regarding allocation of more area to the crops in the long run.

Yu et al., (2012) applied the GMM approach to a balanced panel of 108 counties over the period of 1998–2007. The coefficients of the estimated parameters for the response of grain to its own-price and to the price of oil crops were significant and consistent with standard production theory: a positive supply response to own-price and a negative response to competing crop price. The results reveal that grain acreage was significantly influenced by the prices of wheat and oil crops. When the price of wheat rose by one percent, farmer's chooses to increase the share of their land allocated to grain cultivation by 0.27 percent. When the price of oil crops rose by one percent, farmers were likely to decrease the land share they allocate to grain by 0.20 percent. The responses of cotton area with respect to cotton and oil crops prices were large, suggesting the land allocated for cotton cultivation was more volatile than that of other crops, probably because cotton production was completely market-oriented. They considered total rainfall from the previous growing season for both summer and winter crops. Increased rainfall decreases the land cultivated under cotton and oil crops. This was partly because cotton and oil crops were mostly grown in dry environments and excess soil moisture could hinder crop production. Farmers therefore reduce the area devoted to cotton and oil crops as a short-term strategy to adapt to excess rainfall.

Kavinya and Phiri, (2013) conducted a study to explore the nature in which smallholder maize producers respond to price and non-price incentives employing an Auto-regressive Distributed Lag model using time series data for the period 1989 to 2009. The results showed that the important factors affecting smallholder farmers' decision to allocate land to maize included the lagged acreage allocated to maize, availability of labor and inorganic fertilizer. Lagged maize prices and weather (annual rainfall) were found to be statistically insignificant in influencing farmers' decision to allocate land to maize. They concluded that price incentives on their own were inadequate to influence smallholders' decision to allocate land to maize because farmers were largely constrained by land and cash resources. These constraints were further creating the problems to hire labor and to purchase inorganic fertilizer in order to respond to higher market prices. Therefore policy reforms needed to go beyond market and price interventions as a means of incentivizing staple food production in Malawi.

The above literature showed that the earlier researcher mostly estimated impact of temperature variability and acreage response on cereal crops and there estimation were at geographically aggregated basis (Ashfaq et al., 2011b). Climate change is an overtime study of climatic variables. In Pakistan, most of the researchers conducted their studies without being considering the definition of climate change, like (Shakoor et al., 2011) estimated the impact of climate change (in fact temperature variability) on agriculture using 12 years data set while Ashfaq et al., (2011c) and Mahmood et al., (2012b) conducted their studies on geographically aggregated basis. Research finding showed that estimation of effect of climate change on geographically aggregated basis nullified the effect of climatic variable on yield (Shaw, 1964a). Indeed, it is a need of the time to fill this gap of research and measure the impact of climate change on other cash crops at geographically more disaggregated level in Pakistan.

The available literature in the context of Pakistan showed that many researchers used time trend variable to capture the effect of overtime technological improvement. Whereas, research showed that incorporating a linear or quadratic time trend as a proxy for developments in crop production technology is incorrect because these are correlated with level of CO_2. Furthermore, unraveling time and CO_2 effects is difficult because of the almost perfect collinearity between time and atmospheric CO_2 plus the small variation of atmospheric CO_2 concentration across locations. Therefore, the time trend variable may implicitly capture both the effect of CO_2 fertilization and technological progress. Zepeda, (2001b) suggested that the agriculture R&D expenditure could be used as a proxy for the agricultural technology change. This study differs from others in the following ways. We intend to estimate responsiveness of both yield and sugarcane acreage (in Pakistan) to climatic factors and socioeconomic variables using data disaggregated at the district level. While controlling for other important variables, the study would analyze the effect of climate change (long run changes in temperature and precipitation) as well as weather shocks (deviation of temperature and precipitation from long run norms) on sugarcane yield and acreage allocation. The study will also capture the effect of drought and R&D expenditure on sugarcane crop in Pakistan.

Chapter 3

Methodological Framework

3.1 Introduction

This study is guided by the conceptual framework of farmers' response to price and non-price factors which is given in Figure 3.1. It is clear that there are different price and non-price factors which effect the sugarcane yield in Pakistan. This study follows the following conceptual framework to quantify the responsiveness of sugarcane yield and acreage to climate change in Pakistan at districts level. Later section of the chapter is divided on the theoretical framework for climate change and yield response model and climate change, price and acreage response model for sugarcane crop.

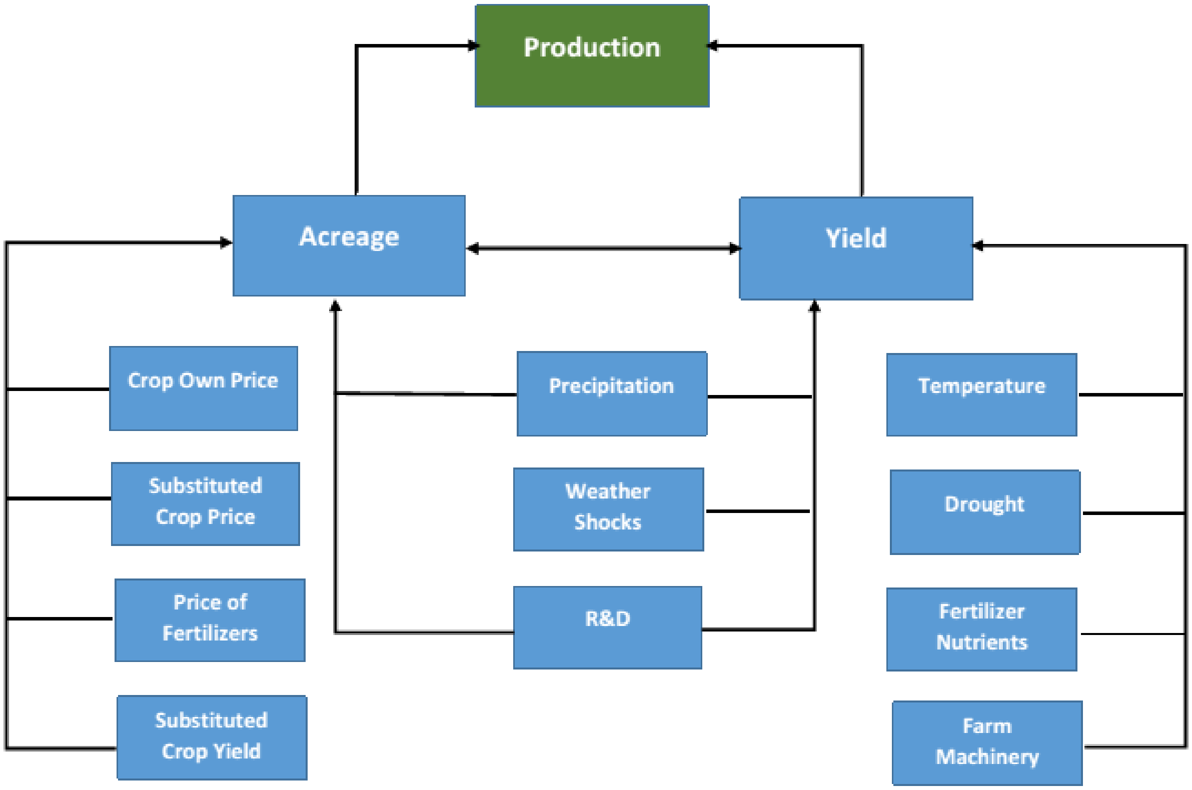

Figure 3.1: Different Factors Influencing the Sugarcane Yield

Pakistan is blessed with fertile lands and all the four seasons which are suitable to grow a variety of crops including food, fiber, and cash crops. Table 3.1 shows crop calendar for different food and cash crop of Pakistan. It can be seen from the crop calendar that sugarcane crop is facing competition from wheat and cotton (Bt.) for the land and resources. Any drastic change in the agriculture support price for wheat and cotton crop has increased the area allocated to these crops as well as production but at the cost of the sugarcane crop. This will distort the equilibrium of demand and supply of sugarcane in the country.

Table 3.1: Crop Calendar of Different Crops in Pakistan

Crop (s)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Sugarcane	Harvesting Sowing										Harvesting	
Wheat				Harvesting							Sowing	
Cotton (Conventional)				Sowing					Picking/Harvesting			
Cotton (Bt.)		Sowing						Picking/Harvesting				
Maize (Spring)	Sowing			Harvesting								
Maize (Autumn)							Sowing		Harvesting			

Source: PARC and AARI

The shares of crop acreage in total cropped area[12] under 5 major crops in 20 main sugarcane producing districts of Pakistan are presented in Table 3.2.

Table 3.2: Share of Crop Acreage in Total Cropped Area under Major Crops Grown

Crop(s)	Area (%)			
	Punjab	Sindh	KPK	Pakistan
Sugarcane	9.6	13.0	19.5	14.03
Cotton	19.7	27.4	0.3	15.82
Wheat	53.8	44.8	54.2	50.93
Rice	11.9	14.1	1.9	9.31
Maize	4.9	0.7	24.1	9.91
Total	**100**	**100**	**100**	**100**

Source: Author's own calculation

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[12] 1981-2010

It confirms that in our study area wheat and cotton is the major competing crops for sugarcane respectively accounting for 50.93 percent and 15.82 percent acreage in total cropped area under major crops.

3.2 Climate Change Yield Model

The climate change impacts on agricultural production bears a great debate about its theoretical and numerical representation (Mendelsohn and Dinar, 1999; Mendelsohn et al., 1994). There are different approaches to study impact of climate change on agricultural production suggested and followed by various researchers including the Ricardian approach, production function approach and agronomic crop simulation models (Mundlak, 1978a; Mundlak et al., 2008; Mundlak et al., 1999a). Mendelsohn established the Ricardian approach to measure the effect of climate change on agricultural land values. Theoretical pinning of Ricardian framework showed that land value is the implicit value of discounted profit received by land which could represented by land rent. Land rent for any agricultural land depicts the productivity of land, location of land etc. The land values usually do not correctly depict the land productivity due to the imperfection of land market. Schlenker and Roberts, (2006) reports the critiques on the Ricardian framework on the basis of its failure to account the cost of adjustment to climate change as well as it is a cross-section analysis so does not incorporate the effect of price variation so underestimate the impact of climate change and have omitted variable bias or model misspecification. Another critique on Ricardian approach is that it uses the extensive farm level data which is usually not available in developing countries. Although, Agronomic models are mostly used in analysis of the impact of climate change on crop production but these models also have certain limitations. Firstly, these models use the data of physiological process and most variability is explained by non-linear forms of these variables. It is difficult to interpret the results due to the non-linearity of variables. Secondly, the problem is that model treats all the information about the production function as exogenous so neglect the adaptive response of farmers.

The history of the production function approach starts from (Solow, 1956) and extended by many researchers for panel data analysis. Mundlak (2001 & 2011) and Mundlak et al. (1999b) used production function approach to measure the effect of environmental input on agricultural production. But main feature of production function approach is that all the explanatory variables are exogenous, error term has no effect on the explanatory variables, so chance of endogeniety will be minimized.

The study of production function for agriculture has a very long history. The farmers will be price takers as input and output prices are given because of pure competition in both markets including input and out market. Profit will depend upon both the price and quantity of the output, higher the both higher will be profit. But the established production function explained by Solow, (1956). The output is the function of inputs employed in production and the productivity of output, determined by calculating the productivity of all inputs. The relationship between the output and input is completed by the inclusion of technology factor which is adapted to during production function, so the simplest functional form for production function could be symbolized as following

$$Y = f(X) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (3.1)$$

Y is the output produced under some technology by using a vector of inputs (X) including conventional inputs, climatic factors and other socioeconomic variables . For this analysis of climate change we assume that technology; choice set for production of a crop do not vary across various cross-sections (districts/counties etc.) of a country. So introduction of any new technology will almost be available to farmers of all the units (districts/counties). The efficiency of input use and technology is affected by the climatic condition and the soil characteristic of the specific area (Deressa, and Hassan, 2009). Therefore, problem in selecting the level of input use depends upon the selected district's cropping area so climate variables in this model are treated as state variables which determine the other variables. Solow (1956) studied the economic growth of economy by introducing the broader definition of capital and labor as inputs but in agriculture these broad terms are disaggregate into inputs which have great importance for agricultural production (Mundlak et al., 1999c). For panel data, simplest functional form of production function can be written as following

$$Y_{it} = f(X_{it}) + \mu_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (3.2)$$

Where i represent districts (1, 2, 3,… n), t denotes year (1, 2, 3,..., T), Y represents yield and X is quantity of inputs. All the variables have panel data representation, Y_{it} is the vector of output representing yield of sugarcane in district i during the year t., X_{it} is matrix of control and state variables and u_{it} is panel data disturbance term which is different from time series or cross-section disturbance term. As production function (Y_{it}) associated with the technique, where production function is concave and twice differentiable, and define the available technology; as the collection of all possible techniques (Mundlak et al., 1999d).

$$u_{it} = \alpha_i + v_t + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (3.3)$$

The disturbance term (u_{it}) can be divided into three elements[13], 1st element (α_i) is due to cross-section, the 2nd element (v_t) is due the time effect and 3rd element (ε_{it}) is stochastic due to formation of panel data. Cross-section and time wise effects may lead to the fixed effect

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[13] See Mundlak, et al (1999)

(heterogeneity of panel data) or random effect model for estimations. The production function differ in their factor intensity imply different β_s . Therefore, we can write the production function as

$$Y_{it} = X(s_{it})\beta(s_{it}) + u_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (3.4)$$

Whereas s_{it} is a vector of state variables that potentially vary over time and location.
The marginal impact of climate change variables can be simply calculated by taking the derivative of production function with respect to climate inputs (C_{it}) which is as follows

$$\frac{\partial Y_{it}}{\partial C_{it}} = \frac{\partial f(X_{it}, C_{it})}{\partial C_{it}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (3.5)$$

3.2.1 The Palfai Drought Index

For numerical characterization of droughts, the Palfai drought index (PaDI) has been used by the researchers in agricultural production and water management studies. This index exemplifies the strength of the drought for an agricultural year with one numerical value, which has a strong relation with performance of a crop (success/failure). The present study uses the drought index for the first time for estimation of production function of Pakistan's agriculture (following Lee and Nadolnyak, (2012) who used Palmer Drought Severity Index (PDSI) for USA).

However, three correction factors were used in Palfai Aridity Index (PAI) and factors based on daily temperature and precipitation values, as well as groundwater levels that is much difficult. For easier practical use, Palfai and Herceg, (2011) have worked out a new, simpler method for the calculation of these factors, which is based on monthly mean air temperature and monthly sum of precipitation.

Following is the formula of the base-value of the modified index,

$$PaDI_{\circ} = \frac{\left[\sum_{i=apr}^{aug} T_i\right]/5 * 100}{c + \sum_{i=oct}^{sep}(P_i * w_i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (3.6)$$

Whereas

$PaDI_o$ = base-value in °C/100 mm

T_i = monthly mean temperature (°C) from April to August

P_i = monthly sum of precipitation (mm) from October to September

w_i = weighting factor

c = constant value (10 mm)[14]

The weight factors (w_i) of precipitation are given in Table A.2 (Appendix 2). These weights shows the difference between the moisture accumulation in soil and the water demand of plants.

3.2.1.1 Calculation of Drought Index Correction Factors

There are three correction factors used for drought index. These are k_1, k_2 and k_3. Moreover, k_1 characterize the relation between examined and annual summer mean temperature, k_2 represent the relation between examined and annual summer precipitation sum from temperature and precipitation correction factors respectively while k_3 symbolize the effect of precipitation circumstances of previous 36 month. .

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[14] Measured drought index based on 10 mm precipitation for longer period of time

The k_1 used as temperature correction factor which represents the number of hot days. The calculation of k_1 is as follows:

$$k_1 = \frac{\left(T_{jun} + T_{jul} + T_{aug}\right)/3}{\left(\overline{T_{jun}} + \overline{T_{jul}} + \overline{T_{aug}}\right)/3} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.7)$$

Whereas:

k_1 – Temperature correction factor,

$T_{jun,\,jul,aug}$ - Mean temperature (°C) for June, July, and August in given year,

$\overline{T}_{jun,\,jul,aug}$ - Long term mean temperature (°C) for June, July, and August (for period 1981-2010)

The k_2 used as precipitation correction factor which represents the length of rainless period. Calculation of K_2 is done using the following formula:

$$k_2 = \sqrt[4]{\frac{2 * \overline{P_{sum}^{min}}}{MIN\left(P_{jun}, P_{jul}, P_{aug}\right) + \overline{P_{sum}^{min}}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.8)$$

Whereas:

k_2 – Precipitation correction factor,

$\overline{P}_{sum}^{\min}$ - The lowest value from multiannual precipitation (mm) sum of three summer months (June, July, August)

$MIN(P_{jun}, P_{jul}, P_{aug})$ - The lowest value from annual precipitation (mm) sum of three summer months (June, July, August)

The k_3 used as groundwater circumstances correction factor which represents groundwater circumstances. Here calculation is based on previous 3 years precipitation values:

$$k_3 = \sqrt[n]{\frac{\bar{P}}{\overline{P_{36month}}}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(3.9)}$$

Whereas:

k_3 –characterizes the precipitation circumstances of the previous period, Correction factor, which

$\bar{P}$ - Average multiannual precipitation (mm) sum for period October-September

$\bar{P}_{36m}$ - Average precipitation (mm) for October-September for previous 3 years[15]

n - Exponent value is 3.0 on the plain area, on hilly or higher territories is 5.0[16].

3.2.1.2 Calculation of PaDI

$$PaDI = PaDI\circ \; * k_1 * k_2 * k_3 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . \dots\dots\dots\dots\dots\dots \text{(3.10)}$$

$PaDI$ = Palfai Drought Index, °C/100 mm

k_1 = temperature correction factor,

k_2 = precipitation correction factor

k_3 = correction factor, which characterizes the groundwater circumstances of the previous 36 month

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[15] 1978-1980

[16] Values based on water level in the soil layer

For all the major sugarcane producing districts of Pakistan, we will determined the PAI and PaDI values for the period 1981-2010. The wider classification of drought strength is shown in Table A.3 (Appendix 3).

3.3 Climate Change and Acreage Response Model

Most of the researchers to quantify the response of acreage to crop price(s). Sangwan, (1985c) quantified the response of crop acreage to various factors including crop price and weather (rainfall) in cropping patterns of Haryana State, India. He studied 13 crops comprising cash, food, oilseed and vegetable (Potato) crops. Although, he failed to report the response of weather for cash crops like sugarcane in his study due to superior methodology and estimation problems. Moreover, Aruna and Upender, (2012b) calculated the response of groundnut crop acreage to price for Andhra Pradesh, India. They didn’t incorporate the important explanatory variable climate to get the exact estimate under changing environmental conditions.

However, few researchers try to improve the methodology including Mushtaq and Dawson, (2002c) used superior methodology (here used co-integration approach) to quantify the response of crop acreage to prices and other important factors in Pakistan. Although, they didn’t intentionally or unintentionally incorporate the climatic variables in their study. Although, there are some studies available that used the climatic variables to quantify the response of crop acreage including Kanwar, (2004b) in India for different crops (including cotton and sugarcane also). In conclusion, there is a need to conducted a study that superior in methodology, consider the climatic variables (variable construction based on principal definition of climate change) and focused on cash crop (here sugarcane) to achieve the specific objective of our study.

For this study, a linear functional form was used for acreage response model. The inclusion of lagged acreage, input and output price variables as independent variables in the model may create an endogeniety problem. In addition, the presence of lagged dependent variables also gives rise to autocorrelation. To appropriately take care of the issues inherited in such a dynamic panel data model with a relatively short time dimension and a large cross-section dimension, a fixed-effect Arellano-Bond difference GMM estimator is used (Arellano and Bond, 1991). Instrumental variables used in the Arellano-Bond GMM estimation include lagged monthly mean precipitation at different sugarcane phenological stages to control the problem of serial correlation. Past weather was included due to their potential influence on price expectations and therefore on crop acreage/yield decisions. Moreover, past weather was included because it is exogenous and varies widely across locations and time and can affect expected prices by affecting inventories (Roberts and Schlenker, 2010).

Chapter 4

Data and Methodology

4.1 Introduction

The panel data is used in this study for analysis. The empirical analysis is based on the cross-section data of twenty major sugarcane producing districts of Pakistan[17] for the time period between 1981 and 2010. The selection of district was based on three considerations: a) presence of meteorological observatory since early 1960s; b) contribution of the district to sugarcane production; and c) the year of creation of the district[18] (in 1980-81 or earlier). Out of the selected districts, 09 are from Punjab, 08 from Sindh and 03 from Khyber Pakhtunkhwa (KPK). This chapter is divided into two section, one for climate change yield response model and other is for acreage response model for sugarcane crop.

4.2 Climate Change and Yield Response Model

4.2.1 Data and its Sources

This study uses two type of variables, climatic variables and other socioeconomic variables. The data sources of various variables are discussed below. Inter alia, climate is an important variable. This study uses district level temperature and precipitation data as climatic variables retrieved from Pakistan Meteorological Department. For other socioeconomic variables, data of selected districts of Pakistan, on variables such as yield, proportion of irrigated area, number of tractors and fertilizer

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[17] Please see Table A.1 (Appendix 1)

[18] Several new districts were created in Pakistan during the period 1981-2010, the statistics regarding these districts for the years prior to their creation were never worked out by the concerned quarters and therefore are not reported. This left us with no choice but to merge the available data in parent districts. In addition, this action also helped in balancing the panel.

nutrients uptake (NPK nutrients) in the model were obtained from Pakistan Bureau of statistics (PBS). Further description of the climatic variables and respective data sources are explained in the Table 4.1.

Table 4.1: Details of the Variables Used in Climate Change and Yield Response Model

Variables	**Source**	**Unit**
Yield	PBS*	Tonnes per hectare
Proportion of Irrigated area	PBS*	Ratio of irrigated area to cultivated area
Fertilizer	PBS*	NPK Nutrients kg per hectare
Area	PBS*	(000) Ha
PaDI	Palfai and Herceg (2011)	Based on seven categories
R & D	Research and Development (R&D) Expenditure on Sugarcane	Million rupees
Precipitation	PMD**	Monthly mm
Temperature		Monthly mean temperature °$_C$
Shocks in precipitation	Author’s own calculation	Deviation from long term means
Shocks in temperature	Author’s own calculation	

* Pakistan Bureau of Statistics; ** Pakistan Metrological Department

4.2.2 Construction of the Variables

The dis-aggregated level of yield [the net production/cropped area] of the sugarcane is used as the dependent variable for the each districts of Pakistan. Moreover, the set of socioeconomic variables comprises of all the important variables that directly related to the yield of the sugarcane crop in each districts including cropped area, total number of tractors and fertilizer (NPK nutrients) were used as explanatory variables in the yield model based on the theoretical validation about the importance of variable (Schlenker and Roberts, 2008; You et al., 2009).

Some early studies argued that for the use of less geographically aggregated meteorological data nullified the casual relationship between crop yield and climatic factors when yield and climatic variables are averaged at higher levels of spatial aggregation (Shaw, 1964b). Therefore, twenty years monthly means moving average[19] is used to know the impact of climate change on sugarcane yield. Moreover, as we know that temperature and precipitation are important climatic variables; crop yield is usually sensitive to temperature and precipitation fluctuations. Although, temperature values are usually not vary too much during the sugarcane production season but crop optimal temperature changes for each growth stage. In conclusion, climatic variables (temperature and precipitation) are computed at disaggregated level according to the sugarcane phenological stages. According to the national sugarcane experts[20], there are following four main stages with their duration for sugarcane crop[21] (Table 4.2).

Table 4.2: Phenological Stages of Sugarcane Crop

Phenological Stages	**Months**
Sowing and Germination Stage	Jan-Mar.
Tillering Stage	Apr.- Jun
Grand Growth Stage	July – Aug
Maturity and Harvesting Stage	Oct-Nov

Source: PARC and AARI

It is evident that most of the crops have an optimum temperature in each growth stage, at which their yields are greater than that at above and below optimum temperatures. The literature shows

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[19] Twenty years moving average were used for our dataset e.g. for 1981 monthly data moving average of 1960-1980 were used

[20] Agricultural Economist, Coordinator Sugarcane Programme

[21] Sugarcane sowing and harvesting dates are varies among different provinces. Therefore, these month(s) for different phenological stages are adjusted for different provinces after consulting with sugarcane experts.

that yields are a quadratic function of average temperatures in simple model. The quadratic model, however, shows gradual increase and symmetry on the temperature-yield relationship. The increase in yield reported up to the optimum temperature and decline at the same smooth rate as temperatures rises (Ackerman and Stanton, 2012b). Therefore, square terms of climatic variables (precipitation and temperature) are used for this study. For this study, deviation of current temperature and precipitation from long term norms used as weather fluctuations to capture the effect of climatic variability (Chen, and Chang, 2005a).

Similarly, present study used sugarcane cropped area and proportion of irrigated area (irrigated area/cultivated area) to know their effect on sugarcane crop yield based on Calzadilla et al., (2013). Fertilizer is an important input in agriculture production process to increase the agriculture crop yield. District level fertilizer usage data is not available. Therefore, present study used district level fertilizer uptake (NPK nutrients kg per hectare) for sugarcane crop. District wise share of the sugarcane crop in fertilizer uptake is calculated from the data retrieved from National Fertilizer Development Center (NFDC). Moreover, total number of tractors in each districts were used to know the effect of farm mechanization on sugarcane crop yield. According to Malik, (2010), the phosphorous (P) is a critical nutrient for maturity and also for the sugarcane crop yield. Therefore, in present study we used P into NPK fertilizer nutrient ratio to know the effect of P nutrient on sugarcane crop yield.

Zepeda, (2001c) suggested that the agriculture research and development (R&D) expenditure used as a proxy for the agricultural technology change. Hence, agricultural R&D expenditure (average of previous eight years)[22] on sugarcane crop is used to capture the effect of production technology on sugarcane crop yield.

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[22] As crop varietal development required at least eight years continuous Research & Development. Therefore, we used eight years average to know their impacts on yield of sugarcane crop.

4.3 Econometric Model

The present study followed the panel data estimation technique used by Siddiqui et al., (2012). For the panel data estimation, there are two widely known model, named accordingly to the nature of an effect if it is fixed then fixed effect model and vice versa.

- Fixed Effect Model
- Random Effect Model

4.3.1 Fixed Effect Model

These unobserved effects could be time-wise or cross-section wise depending upon the characteristics of the sample. In agriculture this unobserved effect is usually time-invariant because of the agro-ecological characteristics of the specific area in the different time horizons. In error term form this can be written as[23]

$$Y_{it} = \beta_0 + \beta_i X_{it} + U_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.1)$$

$$U_{it} = \alpha_i D_i + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4.2)$$

$$Y_{it} = \beta_0 + \beta_i X_{it} + \alpha_i D_i + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.3)$$

Where X_{it} contain the explanatory variables like cropped area, total number of tractors and climatic variables etc., α_i is vector effect of X_{it} on conditional Y_{it}, effects are denoted by $\alpha_i D_i$[24], α_i is called as individual effect or individual heterogeneity and dummy (D) capture the characteristics which are specific to district climatic condition, soil attributes and other knowledge of farm practices which makes the district different from others. Fixed effect model also shows that fixed term in this model is correlated with explanatory variables (cross-section specific characteristics). In

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[23] Wooldridge, 2002

[24] Mundlak, 1978

agriculture mostly fixed effect model (Lee and Nadolnyak, 2012) are used in the panel data study if the sample is not chosen randomly (Wooldridge, 2002).

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{pmatrix}_{NT*1} ,D = \begin{pmatrix} i_T & 0 & \cdots & 0 \\ 0 & i_T & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdots & i_T \end{pmatrix}_{NT*N} ,X = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1k} \\ X_{21} & X_{22} & \cdots & X_{2k} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ X_{N1} & X_{N2} & \cdots & X_{Nk} \end{pmatrix}_{NT*k} \ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots..(4.4)$$

And

$$\alpha = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{pmatrix}_{N*1} ,\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{pmatrix}_{k*1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4.5)$$

Here Y is the matrix of dependent variables, X is the matrix of independent variables and D represents the dummy variable for each cross section.

4.3.2 Random Effect Model

In the parlance of econometrics, the selection of fixed or random effect is determine by the way through which the unobserved effect is viewed. If unobserved effect beheld as random variable then random effect or act as parameter then estimated as fixed effect. Fixed effect models are free from heterogeneity bias and mostly used in the panel data in which the difference in the firms are firm or district specific. So, the heterogeneity is the reason of some area specific characteristic just like land or by management bias (Mundlak, 1961). When unobserved effect, which require the strong assumption of orthogonality in v_i and X_{it}, is treated as random variable then the random effect model is applied which as following

$$Y_{it} = \beta_0 + \beta_i X_{it} + U_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.6)$$

$$U_{it} = v_i + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (4.7)$$

$$Y_{it} = \beta_0 + \beta_i X_{it} + v_i + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.8)$$

But the random effect model usually required a strong assumption that the correlation between explanatory variables and random effect must be zero[25].

$v_i \sim N(0, \sigma_v^2)$

$\varepsilon_{it} \sim N(0, \sigma_v^2)$

$Cov(X_{it}, v_i) = 0$

$Cov(X_{it}, \varepsilon_{it}) = 0$

Therefore, exogenity is usually violated in the random effect model because of measurement or sample selection error and sometimes it may exist because of omitted variable bias. To capture the variance effect, the random effect model is estimated by using GLS but before we move toward GLS estimation the existence of heterogeneity bias must be justified to remove the endogeniety problem analysis of variance is used (Mundlak, 1978b).

To evaluate the effect of heterogeneity in the data fixed effect or random effect model are used but for this case due to cross-sectional heterogeneity fixed effect model will be preferred more and also suggest by the literature but the final decision about which model is most appropriate the Hausman test will be used, after which the model selection criteria’s will be applied to evaluate the model goodness (Hausman and Taylor, 1981).

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[25] Wooldridge, 2002

4.3.4 Empirical Equation

The empirical yield function model[26] that is used in this impact study is as

$$lnY = \alpha_\circ + \sum_{S=1}^{4} \beta_{1S}\,(P_{iSt}) + \sum_{S=1}^{4} \beta_{2S}(P_{iSt})^2 + \sum_{S=1}^{4} \beta_{3S}(T_{iSt}) + \sum_{S=1}^{4} \beta_{4S}\,(T_{iSt})^2 + \sum_{S=1}^{4} \beta_{5S}(DVP_{iSt}) + \sum_{S=1}^{4} \beta_{6S}\,(DVT_{iSt}) + \sum_{S=1}^{4} \beta_{7S}\,(P * T_{iSt}) + \beta_8(PaDI_{it}) + \beta_9 ln(A_{it}) + \beta_{10}(IA_{it}) + \beta_{11} ln(NT_{it}) + \beta_{12} ln(FN_{it}) + \beta_{13}(PFR_{it}) + \beta_{14} ln(R\&D_{it}) + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (4.9)$$

Moreover, some variables are used in their logarithm form to reduce the heterogeneity of the variance and to provide a convenient economic interpretation-elasticity's (Attavanich and McCarl, 2011). Both the linear and quadratic terms for climatic variables are estimated in the model. Therefore, the non-linear relationship between the agricultural production and climate variables will be captured.

Although fixed effects are introduced in this model but we used Hausman test[27] for final selection of model.

$$H = (\beta^{FE} - \beta^{RE})\ [var(\beta^{FE}) - var(\beta^{RE})]^{-1}(\beta^{FE} - \beta^{RE}) \sim X^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (4.10)$$

The Hausman specification test usually checks the existence of fixed or random effect in the model. For test application first we calculate the model using the Random effect model after which we apply the test. Hausman test is based on concept of no correlation (hypothesis) that both OLS and GLS are consistent while OLS is not efficient and under the alternative, OLS is consistent while GLS is not. The proceeds under the null hypothesis the random effect is consistent and efficient

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[26] P = linear form of precipitation, T = linear form of temperature, DV = the deviation from long term norm, P*T = interaction term of precipitation and temperature, A = area of the crop, IA= the proportion of irrigated area to the cultivated area, NT = total number of tractors, FN = fertilizer nutrients uptake, PFR = Phosphorus to total NPK nutrients ratio

[27] Green, 2012

and under alternative hypothesis that fixed effect is consistent. The test statistics will decide that which estimation technique will be used (Hausman, 1978a).

4.3.5 Panel Unit Root

An important thing that must be consider is to check that the series are stationary or not when we are dealing with a series that vary over time. If we are regressing the series of non-stationary with another non-stationary series that may lead to what is known as spurious regression. The results of statistical tests of the parameters from these are biased and inconsistent. The standard approach to investigate the stationarity of a panel series is through panel unit root tests. There are two groups of panel unit root tests, one group treating the persistence parameters $\eta_i = \eta$, that is constant across the cross-section (the Levin, Lin, and Chu (LLC), Breitung, and Hadri tests) and the other group treat these parameters as cross-section specific (the Im, Pesaran, and Shin (IPS), Fisher-ADF and Fisher-PP tests). These tests have their own merits and demerits. The same panel series gave different results with different tests. We use different types of tests namely Levin, Lin and Chu (LLC), Im-Pesaran-Shin test (IPS) and the Fisher-Augmented Ducky Fuller-Chi-square test to check the stationarity of the panel series for precise estimates.

4.3.5.1 Levin, Lin and Chu (LLC) Unit Root Test

The following three alternative models are specify by (Levin et al., 2002)

$$\Delta y_{it} = \eta y_{it-1} + \xi_{it} \dots\dots\dots\dots\dots\dots (4.11)$$

$$\Delta y_{it} = \alpha_{0i} + \eta y_{it-1} + \xi_{it} \dots\dots\dots\dots\dots\dots (4.12)$$

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i} + \eta y_{it-1} + \xi_{it} \dots\dots\dots\dots\dots\dots (4.13)$$

While the error process ξ_{it} is anticipated independent across the cross-sections and follow a stationary ARMA process for each cross-section

$$\xi_{it} = \sum_{p=1}^{\infty} \varphi_{ip}\xi_{it-1} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4.14)$$

Their model comprises of three data generating process.

- In the first model the panel unit root test evaluate the null hypothesis that $H_0 : \eta = 0$ against the alternative that $H_1 : \eta < 0$.
- In the second model the series y_{it} has cross-section specific mean but no trend. In this model the panel unit root test evaluate the null hypothesis that $H_0 : \eta = 0$ and $\alpha_{0i} = 0$ for all i, against the alternative that $H_1 : \eta < 0$ and $\alpha_{0i} \in \Re$.
- In third model the series y_{it} has cross-section specific mean and time trend. In this model the panel unit root test evaluate the null hypothesis that $H_0 : \eta = 0$ and $\alpha_{1i} = 0$ for all i, against the alternative that $H_1 : \eta < 0$ and $\alpha_{1i} \in \Re$.

The test proceeds in three steps,

- Firstly, ADF regressions are carried out for each cross-section in the panel, and two orthogonal residuals are generated
- In the second step the ratio of long run to short run innovation standard deviation for each cross-section are estimated
- In the last step the pooled t-statistics are estimated

4.3.5.2 Im-Pesaran-Shin Unit Root Test

The Im et al., (2003) test proceeds with the following model

$$y_{it} = \alpha_i + \eta_i y_{it-1} + \xi_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (4.15)$$

$t = 1,2,3, \dots\dots\dots\dots\dots , T$

Then the following hypothesis are tested

$H_0 : \eta_i = 1 , \qquad i = 1,2,3, \dots\dots .. , N$

The alternative hypothesis are formulated as

$H_1 : \eta_i < 1 , \qquad i = 1,2,3, \dots\dots\dots\dots .. N_1 ; \eta_i = 1 , i = N_1 + 1, N_1 + 2, N_1 + 3, \dots\dots\dots\dots .. , N$

Im-Pesaran-Shin suggests separate unit root tests for the N cross-sections.

$$y_{it} = \alpha_i + \eta_i y_{it-1} + \sum_{j-1}^{n_i} \varphi_{ij} \Delta y_{it-j} + \xi_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (4.16)$$

The ADF regression is estimated and then the t-statistics are computed for testing $\eta_i = 1$. The test assume that T is the same for all cross-sections so that the mean and variance are the same for all i. So, the IPS test can be applied only for balanced panels. In case of no serial correlation IPS proposes the simple DF t-tests for the individual cross-sections.

4.3.5.3 Fisher-Augmented Ducky Fuller-Chi-square Unit Root Test

The third test that we have used is simply the extension of ADF test for individual series to panel series.

4.3.5.4 Test of Heteroskedasticity

Another important test that we carried out before final estimations is the test for Heteroskedasticity. To this end we used White Heteroskedasticity test. For this purpose we first estimated a fixed effects model and the residuals were obtained. Then the square residuals were regressed on the explanatory variables and their squares as under.

$$
\begin{aligned}
(Resid_{it})^2 = \alpha_{\circ} &+ \sum_{S=1}^{4} \beta_{1S}\,(P_{iSt}) + \sum_{S=1}^{4} \beta_{2S}(P_{iSt})^2 + \sum_{S=1}^{4} \beta_{3S}(T_{iSt}) + \sum_{S=1}^{4} \beta_{4S}\,(T_{iSt})^2 + \sum_{S=1}^{4} \beta_{5S}(DVP_{iSt}) \\
&+ \sum_{S=1}^{4} \beta_{6S}\,(DVT_{iSt}) + \sum_{S=1}^{4} \beta_{7S}\,(P * T_{iSt}) + \beta_{8}(PaDI_{it}) + \beta_{9} ln(A_{it}) + \beta_{10}(IA_{it}) \\
&+ \beta_{11} ln(NT_{it}) + \beta_{12} ln(FN_{it}) + \beta_{13}(PFR_{it}) + \beta_{14} ln(R\&D_{it}) \\
&+ \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots
\end{aligned}
\tag{4.17}
$$

4.3.5.5 Cross Sectional Dependence

Different literature on panel data concluded that panel data sets are expected to exhibit substantial cross-sectional dependence, which may ascend due to the presence of common shocks and unseen components that become part of the error term ultimately (Anselin, 2001; Baltagi, 2008; Pesaran, 2004; Robertson and Symons, 2000). Pesaran, Friedman and Frees test are used to know the cross-sectional dependence in the data, if the result confirms the presence of the cross-sectional dependence than the (Driscoll and Kraay, 1998a) standard error method is used.

4.3.5.6 Driscoll and Kraay Standard Errors

Analyzing large-scale micro-econometric panel data sets has now common in social sciences, and particularly in economics. Panels are attractive since they often contain far more information than single cross-sections and thus allow for an increased precision in estimation. Most of the time, actual information of micro-econometric panels is often overstated since micro-econometric data are probably exhibit all sorts of cross-sectional and temporal dependencies (Cameron and Trivedi, 2005). Therefore, speciously overlooking possible correlation of regression disturbances over time and between subjects can lead to bias statistical inference. The most recent studies that consisting a regression on panel data, therefore adjust the standard errors of the coefficient estimates for possible dependence in the residuals to ensure validity of the statistical results. Nonetheless, presumptuous that the disturbances of a panel model are cross- sectionally independent is often incongruous. Though, it might be problematic to persuasively claim why country- or state-level data should be spatially uncorrelated. Fortunately, (Driscoll and Kraay, 1998b) recommend a non-parametric covariance matrix estimator that harvests heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence.

4.2 Climate Change and Acreage Response Model

4.2.1 Introduction

The methodology for the analysis of acreage response model is the Nerlovian adjustment cum expectation model. The Nerlovian framework is superior to alternate models in that they ease calculating short run and long run responses and the speed of adjustment in moving from actual to desired level of land and other inputs. Further, the alternate model needs comprehensive information on input prices which are challenging to acquire (Mythili, 2012a).

Assuming that farmers have rational price expectations based on their information set, farmers' crop acreage decisions can be described using a typical Nerlovian adaptive price expectations model of three equations (Braulke, 1982a).

$$A_t^{Des} = \alpha_0 + \alpha_1 P_t^{exp} + \mu_i \dots\dots\dots\dots (4.18)$$

$$P_t^{exp} = P_{t-1}^{exp} + \beta\left(P_{t-1} - P_{t-1}^{exp}\right) \dots\dots\dots\dots (4.19)$$

$$A_t = A_{t-1} + \gamma(A_t^{Des} - A_{t-1}) \dots\dots\dots\dots (4.20)$$

where A_t is actual planted acres, A_t^{Des} is desired planted acres, P_t is actual price, $P_t^{\exp}$ is expected price, μ_i is a disturbance term representing the effect of weather and other factors affecting cropland supply, the subscript t is time period, β and γ are the expectation and adjustment coefficients, respectively. As shown in (Braulke, 1982b), by removing the unobserved variables A_t^{Des} and $P_t^{\exp}$ from the model, the reduced form of the actual planted acreage equation can be written as:

$$A_t^{Des} = b_0 + b_1 A_{t-1} + b_2 A_{t-2} + b_3 A_{t-3} + v_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4.21)$$

where b_0, b_1, b_2 and b_3 are parameters determined by a_0, a_1, β and γ equations (4.16)-(4.18) and v_t is a disturbance term related to μ_i. The yield effect of crop land use change together with other technological effects dominates the influence of other factors in determining the long-term yield trends (Lobell et al., 2008).

There is a general dearth of empirical research on how crop acreages respond to climate change. Acreage response studies have typically ignored climate factors and used geographically aggregated time series data to represent the behavior of a representative farmer (Chavas and Holt, 1990). Nerlove, (1956) shows that farmers' expectations of future prices shape their crop acreage decisions and the Nerlovian adaptive price expectations model has become a useful tool for the estimation of agricultural supply functions[28]. The model leads to a reduced form with acreage in a given year expressed as a function of one-year lagged crop price and lagged crop acreages[29].

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[28] Pl see Askari and Cummings, 1977 for a comprehensive review of early applications of the Nerlovian model; and Tegene and Kuchler, 1991 for more recent development of the model

[29] Braulke, 1982

In the available literature, crop acreage response models are typically listed with a log linear functional form for ease of interpretation (Chavas et al., 1983b; Weersink et al., 2010c). Whereas, we use a linear functional form for our acreage models. The inclusion of lagged acreage and input and output price variables as independent variables in the acreage model may create an endogeniety problem. In addition, the presence of lagged dependent variables also gives rise to autocorrelation. To appropriately take care of the issues inherited in such a dynamic panel data model, a fixed-effect Arellano-Bond difference GMM estimator is used. We also control the problem of serial autocorrelation and heteroskedasticity by using the robust estimator. Instrumental variables used in the Arellano-Bond GMM estimation include lagged precipitation at different growth stages, procurement price of crop(s), price of fertilizer price(s) and yield of the competing crop(s) in the district. The competing crop(s) and past weather are included due to their potential influence on price expectations and therefore on crop acreage decisions. Hence, the climate change and acreage response model using a district level panel data set can be written as:

$$\begin{aligned}(A_{it}) = \alpha_0 + \beta_1\left(A_{i,t-1}\right) + \sum_{S=1}^{4} \beta_{2S}\,(P_{iSt-1}) + \beta_3\left(R\&D_{i,t}\right) + \beta_4(OPR_{it}) + \beta_5\left(OY_{i,t-1}\right) \\ + \sum_{D=1}^{3} \beta_{6D}\,(CPR_{it}) + \sum_{D=1}^{3} \beta_{7D}\,\left(CY_{i,t-1}\right) + \sum_{E=1}^{3} \beta_{8E}\,(FP_{it-1}) \\ + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots(4.22)\end{aligned}$$

The details of the variables, its sources and units are explained in Table 4.3. We use a linear functional form for our model.

Table 4.3: Description of the Variables for Acreage Response Model

Variable	Definition	Units	Source
$OY_{i,t-1}$	Own yield of sugarcane crop in ith district in during the year t-1	tonnes/hectare	Pakistan Bureau of Statistics
$\sum_{D=1}^{3}(CY_{i,t-1})$	Yield of Dth substituted crop in ith district during year t-1		
A_{it}	Sugarcane crop acreage in ith district in during the year t	(000) hectares	
$A_{i,t-1}$	Sugarcane crop acreage in ith district in during year t-1		
$\sum_{S=1}^{4}(P_{iSt-1})$	Monthly mean precipitation at Sth phenological stages of sugarcane in ith district in during year t-1	Mm	Pakistan Metrological Department
$R\&D_{it}$	Average Research and Development (R&D) expenditure in ith during last eight year[30]	Million Rupees	Agriculture Research Expenditure on sugarcane Research System
OPR_{it}	Own procurement price of sugarcane crop during year t	Rs./40kg	Pakistan Bureau of Statistics
$\sum_{D=1}^{3}(CPR_{t})$	Relative procurement price of Dth substituted crop during year t		
$\sum_{E=1}^{3}(FP_{it-1})$	Real price of Eth fertilizer in ith district during year t-1	Rs./50Kg bag	

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[30] After constructing R&D variables average of last eight years, we have used 1989-2010 data for the construction of balance panel in yield response model

There has been much debate in recent years about the proper level of official prices for agricultural products in less developed countries like Pakistan. Most of this discussion has revolved around the most appropriate relationship of domestic prices to world price clearly need to have some ability to forecast the effect on production. Forecasting production, however, is not sufficient for those governments which actively intervene in their domestic markets by purchasing a large percentage of the crop. Government or para-statal procurement of agricultural commodities also must be forecast for several reasons. First, marketing boards or food authorities must be provided with credit for purchasing the crop in a timely manner if government policies regarding the enforcement of a guaranteed price are to be effective. Second, sufficient storage space must be set aside for the procured commodity. Third, in many countries the government loses money on every tonne of grain that in handles. Thus, the responsiveness of government procurement to a change in price is important for credit, storage and fiscal policy (Molua, 2010b).

For some commodities, the government procures virtually the entire crop and thus the change in procurement will be approximately equal to the change in production. For staple foods, however, the percentage increase in procurement may be much larger than the percentage increase in production since consumption on-farm is unlikely to increase in proportion to production. The presence of an active private market which handles a substantial share of the crop complicates the analysis, however. Thus, price formation in the private market is important for the government to understand. Therefore for this study, we use procurement price(s) of the crop(s) to make our price response analysis more meaningful instead of using real price or whole sale price(s) of crop.

Literature shows that crop(s) low yield are more responsive to the acreage as compared to high yield. In the presence of yield variable, crop are more responsive to prices (Kurukulasuriya et al., 2006a). In conclusion, researcher needs to include yield of the crop to quantify the real price response on crop acreage. Therefore, we used yield of the sugarcane and competing crop(s) including wheat, cotton and maize in this acreage model for the true estimates.

Chapter 5

Results and Discussion

5.1 Tests of the Data and Model:

An appropriate estimation technique is essential to check the type of the data before carrying out panel estimations. There are many important issues that must be considered before the final selection of the model and estimation. One should know about the data that is stationary or having a unit root. Moreover, individual effect exists or we should assessment for a pool equation (with both common intercept and slopes). Moreover, existence of individual effects further needed that whether they are period specific or cross-section specific (may be both). Although, the overlooked individual effects are fixed constant or randomly distributed; independent of the explanatory variables.

In panel data the issue of cross sectional dependence, the problems of multi-collinearity and heteroskedasticity gain special importance for estimating consistent and reliable results. For the present study, we are using the panel data for both yield and the acreage response model to climate change for sugarcane in Pakistan.

5.1.1 Panel Unit Root Tests

The results of the panel unit root tests for yield response model is presented in Table 5.1. All the tests indicate that most of the variables are stationary at level. Detail description of the variables are given in Table A.4 (Appendix 4).

Table 5.1: Unit Root Test for Sugarcane Yield Response Model

Variable	LLC test	Prob.	IPS Test	Prob.	Fisher-ADF Chi-square	Prob.	Conclusion at level
ln(Y)	-2.8671	0.00	-4.6798	0.00	7.9653	0.00	stationary
P_G	-15.415	0.00	-7.0277	0.00	15.0855	0.00	stationary
P_TIL	-8.7390	0.00	-2.4667	0.01	1.6604	0.05	stationary
P_GGS	-14.295	0.00	-8.4846	0.00	26.7014	0.00	stationary
P_MS	-5.4475	0.00	-7.8961	0.00	20.5043	0.00	stationary
T_G	-27.967	0.00	-5.1832	0.00	10.5225	0.00	stationary
T_TIL	-7.5435	0.00	-8.2037	0.00	29.7329	0.00	stationary
T_GGS	-18.248	0.00	-6.9793	0.00	24.7042	0.00	stationary
T_MS	-5.090	0.03	-7.142	0.00	24.704	0.00	stationary
DV_PG	-5.665	0.00	-10.674	0.00	37.367	0.00	stationary
DV_PTIL	-8.726	0.00	-9.573	0.00	27.090	0.00	stationary
DV_PGGS	-7.010	0.00	-10.711	0.00	39.534	0.00	stationary
DV_PMS	-6.287	0.00	-11.050	0.00	44.514	0.00	stationary
DV_TG	-2.093	0.02	-12.491	0.00	59.931	0.00	stationary
DV_TTIL	-5.314	0.00	-10.492	0.00	35.265	0.00	stationary
DV_TGGS	-8.576	0.00	-10.341	0.00	37.022	0.00	stationary
DV_TMS	-12.277	0.00	-8.912	0.00	23.252	0.00	stationary
P*T_G	-11.309	0.00	-6.646	0.00	12.161	0.00	stationary
P*TTILL	-7.941	0.00	-2.454	0.01	1.665	0.05	stationary
P*TGGS	-14.120	0.00	-8.652	0.00	26.329	0.00	stationary
P*TMS	-3.886	0.00	-8.718	0.00	27.392	0.00	stationary
P_G^2	-14.274	0.00	-6.9176	0.00	13.2220	0.00	stationary
P_TIL^2	-8.2196	0.00	-2.4350	0.01	1.6657	0.05	stationary
P_GGS^2	-15.169	0.00	-8.5941	0.00	25.8683	0.00	stationary
P_MS^2	-3.4360	0.00	-9.2706	0.00	32.5934	0.00	stationary
T_G^2	-13.060	0.00	-4.1829	0.00	4.1694	0.00	stationary
T_TIL^2	-10.717	0.00	-7.3286	0.00	19.5797	0.00	stationary

Variable	**LLC test**	**Prob.**	**IPS Test**	**Prob.**	**Fisher-ADF Chi-square**	**Prob.**	**Conclusion at level**
T_GGS^2	-18.495	0.00	-6.4932	0.00	10.9590	0.00	stationary
T_MS^2	-7.9237	0.00	-5.9237	0.00	9.4063	0.00	stationary
ln(NT)	-1.583	0.06	0.058	0.52	1.359	0.09	stationary
PFR	-5.256	0.00	-7.281	0.00	16.681	0.00	stationary
PADI	-8.920	0.00	-6.310	0.00	-6.310	0.00	stationary
ln(A)	-3.810	0.00	-2.958	0.00	4.882	0.00	stationary
IA	2.724	1.00	-6.854	0.00	28.074	0.00	stationary
ln(FN)	-1.977	0.02	-5.017	0.00	1.398	0.08	stationary
ln(R&D)	4.505	1.00	5.071	1.00	1.542	0.06	stationary

Table 5.2 shows the result of panel unit root test for the variables used for our acreage response model. The result of panel unit root suggested that most of the variables used for acreage response model are stationary at level.

Table 5.2: Unit Root Test for Acreage Response Model

Variable	**LLC test**	**Prob.**	**IPS Test**	**Prob.**	**Fisher-ADF Chi-square**	**Prob.**	**Conclusion at level**
A	-2.73	0.00	-1.58	0.00	2.10	0.01	Stationary
(P_G)$_{-1}$	-4.97	0.00	-5.67	0.00	11.12	0.00	Stationary
(P_TIL)$_{-1}$	-5.99	0.00	-4.12	0.00	4.14	0.00	Stationary
(P_GGS)$_{-1}$	-7.36	0.00	-7.57	0.00	13.62	0.00	Stationary
(P_MS)$_{-1}$	-11.23	0.00	-7.26	0.01	12.66	0.00	Stationary
(C_Price)$_{-1}$	-2.07	0.02	-3.97	0.00	2.77	0.00	Stationary
(W_Price)$_{-1}$	-12.67	0.00	-9.15	0.00	22.91	0.00	Stationary
(M_Price)$_{-1}$	-2.80	0.00	-4.19	0.00	1.63	0.05	Stationary
(S_Price)$_{-1}$	-2.56	0.00	-10.68	0.00	22.99	0.00	Stationary
(R&D)$_{t}$	4.92	1.00	-1.80	0.04	2.28	0.01	Stationary
(Urea_Price)$_{-1}$	4.95	1.00	-4.45	0.00	4.01	0.00	Stationary
(DAP_Price)$_{-1}$	5.91	1.00	-10.21	0.00	33.18	0.00	Stationary
(SOP_Price)$_{-1}$	-4.66	0.00	-6.06	0.00	3.25	0.00	Stationary
(Sugarcane Yield)$_{-1}$	-2.65	0.00	-2.51	0.00	2.97	0.00	Stationary
(Cotton Yield)$_{-1}$	-1.79	0.03	-1.80	0.03	2.48	0.00	Stationary
(Wheat Yield)$_{-1}$	-2.59	0.00	-6.58	0.00	13.64	0.00	Stationary
(Maize Yield)$_{-1}$	-1.65	0.05	-3.24	0.00	2.29	0.01	Stationary

5.1.2 Fixed Effects- versus -Random Effects

The estimation of the model with cross-section specific unobservable effect needed to define that fixed effect model [these unobservable are fixed constant correlated with the other explanatory variables] or random effect model [randomly distributed independent of the explanatory variables]. According to Hsiao, (2003) in Panel data, there is no difference to treat the unobservable effects as fixed or random when time span is large because both the least square dummy variable and generalized least square estimators become the same. However, when time period is finite and cross-section units are large, can make a surprising amount of difference in the estimates of the parameters.

The result of Hausman, (1978b) test are crucial to decide between Fixed Effects and Random Effects Models. Fixed effect estimators are consistent if the cross-sections specific effects are correlated with the explanatory variables whereas the random effects are inconsistent and biased. But the random effects are steady and fixed effects are unreliable if the individual specific effects are independently and randomly distributed of the explanatory variables. Thus the main factor to reflect is to check that whether the individual effects are correlated with the explanatory variables or not. Hausman test is based on the difference between the fixed effects and random effects estimates. A significant difference between fixed and random effects is inferred as indication against random effects model. The null hypothesis of Hausman test reported that there is no robust difference between the coefficients of fixed and random effects estimators.

The fixed effects estimators are reliable under both the null and the alternative hypothesis. The random effects estimators are more effective under the null hypothesis but inconsistent under the alternatives. The rejection of the null hypothesis infers that at least some of the explanatory variables are correlated with the individual specific effects. Therefore, if we used random effects model then our results will be biased. The result ratifies that the fixed effect model is suitable because Hausman test rejects the null hypothesis; random effect is appropriate.

5.1.4 Test of Heteroskedasticity

The $N * R^2$ value of (3529.67) with 20 degrees of freedom, lead to the rejection of the null hypothesis of Homoscedasticity. Thus in our final estimation we will have to take into account the problem of Heteroskedasticity.

5.1.5 Cross Sectional Dependence

The effect of cross-sectional dependence in approximation logically depends on a variety of factors, such as the magnitude of the correlations across cross-sections and the nature of cross-sectional dependence itself. Presumptuous that cross-sectional dependence is caused by the presence of common factors, which are unobserved (and as a result, the effect of these components is felt through the disturbance term) but they are uncorrelated with the encompassed explanatory variables, the standard fixed-effects (FE) and random effects (RE) estimators are consistent, although not efficient, and the estimated standard errors are biased. In this case, different likelihoods ascend in estimation. For example, one may choose to depend on standard FE/RE methods and correct the standard errors by following the approach proposed by Driscoll and Kraay, (1998c). The result of the cross sectional dependence[31] shows that there is a robust cross-sectional dependence in the model under the fixed effect estimation assumption. Therefore, we considered this before estimating the final model.

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[31] Pesaran and Friedman results are significant; coefficients are 5.51 and 63.96, respectively

5.2 Empirical Findings:

5.2.1 Climate Change and Yield Response Model

The estimation result of equation 4.9 presented in Table 5.3 shows that the semi-log function gave the best statistical fit for the data in the regression analysis and the estimated model performed well according to its R^2 statistics; explaining 52% of the variation in sugarcane crop yield (Gbetibouo and Hassan, 2005b). The results indicate that the precipitation has nonlinear effect on sugarcane yield at tillering stage. Surprisingly, this non-linear effect is of bell shape (inverted U). The effect of precipitation is positive on yield of the sugarcane crop up to optimal level (1.29 mm) beyond that the sugarcane yield response is negative to precipitation at tillering stage. The sugarcane crop response vary according to the crop phenological stages. The results of the model demonstrate that the effect of precipitation at germination and grand growth stage is linear and significant. These result support the theoretical evidence that significant amount of water is required to initiate the germination stage of the sugarcane crop earlier. The yield of the sugarcane crop will increase by 0.40 percent at germination stage if there is 1mm increase in precipitation while at grand growth stage; yield decline by 0.21 percent. These results are different with the findings of Siddiqui et al., (2012c) where there is no significant effect of precipitation at various stages of sugarcane crop.

Moreover, the results confirms that temperature effect linearly to sugarcane yield and significant effects shown at germination and grand growth stage. The sugarcane response to 1°C increase in temperature at germination and grand growth stage results in 0.31 percent increase and 0.18 percent decrease in yield, respectively. These results are different with the findings of Binbol et al., (2006b) in Nigeria. Temperature at germination stage improved the germination of the seed that results in higher yield of the crop (Ashfaq et al., 2011d). The previous studies showed that at maturity stage the sweetness starts; requires 10 °C temperature for good quality sugarcane (Siddiqui et al., 2012d). The results of our study shows that the temperature at maturity stage has significant negative effect on sugarcane yield at least 20 percent significance level. The mean temperature at maturity stage calculated for this study is 19.66 °C. Sugarcane yield will decline by 0.25 percent in response to 1 °C increase in temperature at maturity stage. In conclusion, higher temperature affected the sugarcane nodes leads to the low sucrose content formation (Bonnett et al., 2006b). The results confirms that the effect of climatic variables (temperature and precipitation) is linear on sugarcane crop at phenological stages except tillering stage.

Chen, and Chang, (2005b) used variation in precipitation and temperature to know the impact of weather on crop yield. Similarly, in our study we used weather shocks/fluctuations (long term deviation from norm) in precipitation and temperature but disaggregated at different sugarcane crop stages. The estimated result confirms that the high weather shocks/fluctuations in precipitation at grand growth stage and temperature at germination stage are significant positive impacts on sugarcane crop yield but magnitude is not robust. These findings are consistent with the theory that high temperature at germination stage induces seed germination while high precipitation at grand growth stage increase the sucrose content and mass of the sugarcane crop.

The result reveals that the yield response vary to both precipitation and temperature at different crop growth stages. The combined effect of both climatic variables is positive and negative at grand growth and maturity stage, respectively. Therefore, due to increased combined effect[32]; yield of the sugarcane crop will show 0.007 percent increase and decrease at grand growth and maturity stage, respectively.

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[32] 1 unit increase in temperature and precipitation, simultaneously

Drought is one of the critical climatic factors that adversely affect the crop yield and its affect vary according to the nature[33] of the crop. The results are suggestive of a significant negative effect of drought on sugarcane yield. These results are similar with the findings of Ahmed and Schmitz, (2011b) for Pakistan. The climate change altering the rainfall patterns may causing water stress induced by drought. Frequent droughts due to climate change will have a negative effect on sugarcane as the crop requires a lot of water and drought lowers the accessibility of water contents in the soil induced water stress results in lower sugarcane yield ultimately (Chandiposha, 2013; McCarl et al., 2008).

Table 5.3: Result of Climate Change and Yield Response Model (Fixed Effect Estimation)

Independent Variable	**Coefficient(s)**	**Independent Variable**	**Coefficient(s)**	**Independent Variable**	**Coefficient(s)**
P_G	0.3989* (0.1286)	**T_TIL^2**	0.0112 (0.0084)	**P*T_GGS**	0.0069** (0.0030)
P_TIL	0.0583** (0.0301)	**T_GGS^2**	-0.0180 (0.0125)	**P*T_MS**	-0.0070** (0.0033)
P_GGS	-0.2069* (0.0784)	**T_MS^2**	0.0076 (0.0070)	**PaDI**	-0.0239** (0.0099)
P_MS	-0.0488 (0.0511)	**DV_PG**	-0.0005 (0.0008)	**lg(A)**	0.4947* (0.1039)
T_G	0.3046** (0.1299)	**DV_PTIL**	0.0002 (0.0005)	**IA**	0.2472 (0.1860)
T_TIL	0.3792 (0.2421)	**DV_PGGS**	0.0003* (0.0002)	**lg(NT)**	0.0298 (0.0690)
T_GGS	-0.1794** (0.0844)	**DV_PMS**	-0.0009 (0.0010)	**lg(FN)**	0.1051* 0.0322
T_MS	-0. 2522	**DV_TG**	0.0074***	**PFR**	0.2303

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[33] Cash crop, oil seed crop, fodder crop etc.

Independent Variable	**Coefficient(s)**	**Independent Variable**	**Coefficient(s)**	**Independent Variable**	**Coefficient(s)**
	(0.1761)		(0.0039)		(0.2987)
P_G^{2}	0.0022 (0.0079)	**DV_TTIL**	0.0024 (0.0094)	**ln(R&D)**	0.0872* (0.0312)
P_TIL^{2}	-0.0012*** (0.0006)	**DV_TGGS**	-0.0130 (0.0136)	**Constant**	-0.3311 (15.384)
P_GGS^{2}	-0.0001 (0.0002)	**DV_TMS**	0.0086 (0.0107)	**R-squared**	0.5208
P_MS^{2}	0.0036 (0.0021)	**P*T_G**	-0.0325 (0.023)	*significant at 1%; **significant at 5%;***significant at 10% Heteroskedasticity-robust t-statistics are in parentheses	
T_G^{2}	-0.0208 (0.0126)	**P*T_TILL**	0.0008 (0.0015)		

Hanif et al., (2010b) estimated that the area under cultivation have positive but insignificant effect on average annual market sale price of agriculture land[34]. Whereas, the result of this study indicated that the relationship between cropped area and yield is positive (Table 5.3). Therefore, any increase (percentage) in the cropped area brings increase in yield (exactly the half of the area). Similarly, the effect of proportion of irrigated area to the total cultivated area in each district have insignificant positive effect. The proportional irrigated area is insignificant may be due to smaller in proportion as compared to the total cultivated area (Huang and Khanna, 2010).

Numerous studies showed that adoption decisions influence with soil and water conservation technologies (Barbier, 1998; Lapar and Pandey, 1999; Pender and Kerr, 1998). Kurukulasuriya and Mendelsohn, (2006b) reported that possession of heavy machinery have robust positive

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[34] Represents the agriculture productivity

impacts on net farm revenue on African cropland. This study supposes that ownership of more farm assets (land and machinery) enhance farmers' ability to adapt. In our case the number of tractors available in each districts have insignificant positive effect on the sugarcane crop yield. Insignificant results may be due to taking the variables of total available tractors instead of tractors owned by sugarcane cultivators in each districts.

Fertilizer nutrients (NPK) is important for the enhanced crop(s) production. Malik, (2010) reported that the recommended fertilizer (NPK) ratio for sugarcane crop is 2:1:2. Whereas, the result reveals that sugarcane crop receives fertilizer nutrients (NPK) in imbalance proportion. The calculated NPK ratio for sugarcane crop in Pakistan at district level is 8.1:1.8:0.1. The enhanced yield of the sugarcane crop, increased their farmer's profitability and improved sustainability depends upon the 4R framework of nutrient stewardship to attain cropping system goals. To achieve those goals, the 4R concept required the: Right fertilizer source at the Right rate, at the Right time and in the Right place. The result confirms that the fertilizer has the robust positive impact on sugarcane yield whereas the phosphorus ratio didn't influence the sugarcane yield significantly. The sugarcane crop receives the imbalance used of fertilizer, therefore the impact of phosphorus is insignificant. In our climate change model, we consider the agricultural technology as a variable instead of considering the constant and/or including time trend. The sugarcane yield respond significantly positive to the investment in agriculture R&D.

5.2.1.1 Marginal Impacts of Climate

To further compare the differences in coefficient estimates of climate models, we calculate their marginal impacts ($\frac{\partial log y_{it}}{\partial z_{it}}$), at the sample mean on sugarcane yield.

Table 5.4: Marginal Effect of Climatic Variables

Precipitation	**Impacts**	**Temperature**	**Impacts**
P_G	0.1031* (0.0363)	**T_G**	0.0616* (0.0190)
P_TIL	0.0226** (0.0100)	**T_TIL**	0.1052 (0.0620)
P_GGS	-0.0490* (0.0160)	**T_GGS**	-0.0399** (0.0256)
P_MS	-0.0010 (0.0114)	**T_MS**	-0.0488 (0.0400)

Standard errors in parentheses; 2. *** p<0.01, ** p<0.05, * p<0.1

The marginal impact measures how changes in climate variables Z_{it} (Precipitation and temperature) affect log crop yields ($logY_{it}$). The result confirms that the marginal impact of both temperature and precipitation on sugarcane yield is positive at germination and tillering stage whereas grand growth and maturity stages temperature and precipitation influence negatively (Table 5.4).

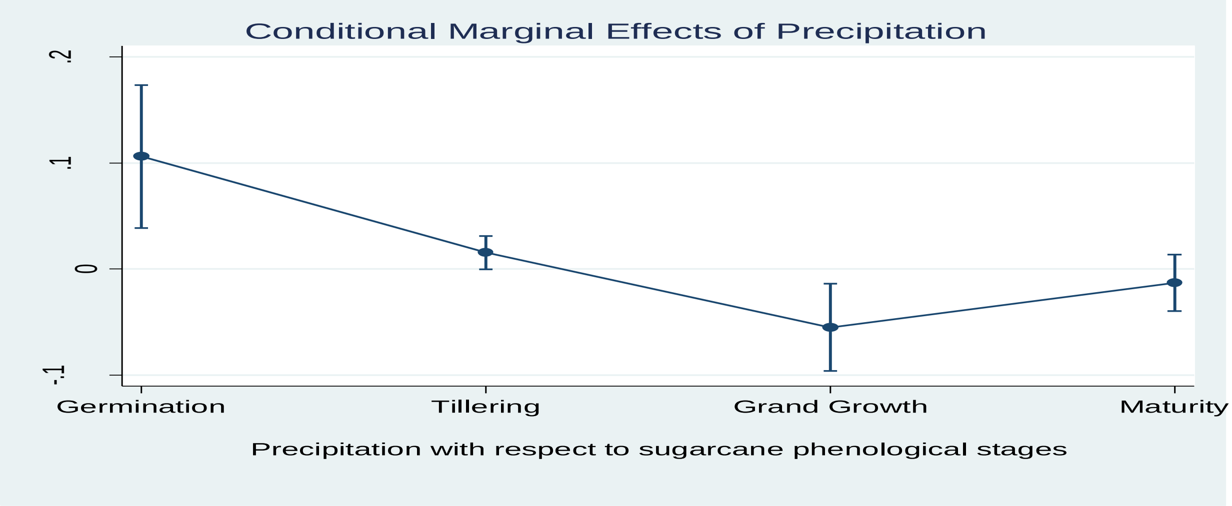

Figure 5.2 Marginal Effect of Precipitation

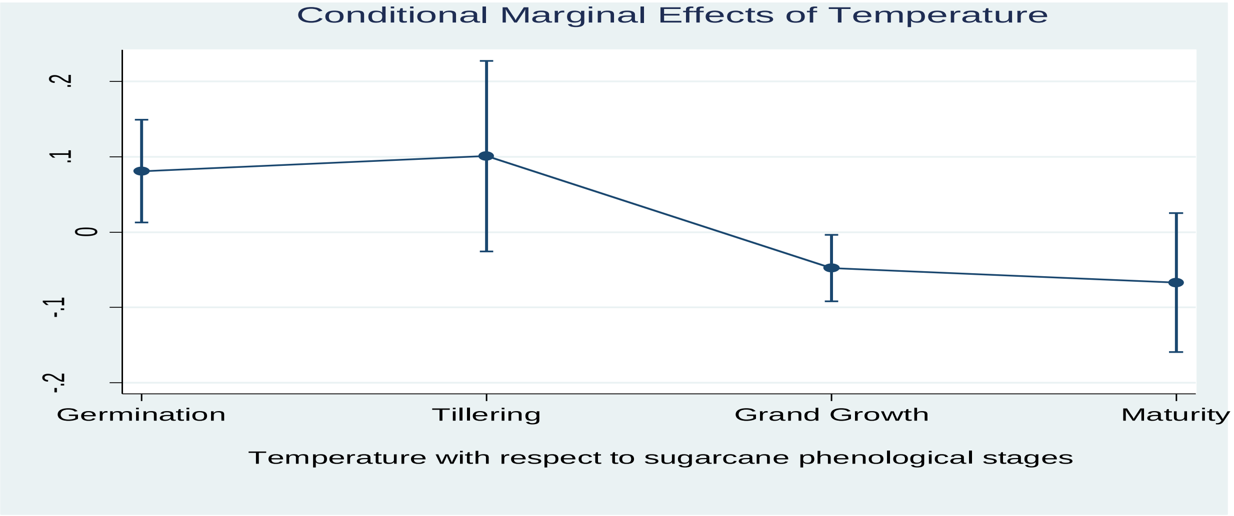

Figure 5.3 Marginal Effect of Temperature

The estimated results indicate that 1mm increase in precipitation at germination and tillering stage significantly increase sugarcane yield by 0.10 percent and two percent, respectively. Moreover, at grand growth stage sugarcane yield showed negative response by 0.4 percent to one unit increase in precipitation (Figure 5.2). However, the yield respond vary in magnitude to temperature at different stages. Initial stages of the sugarcane crop respond positively and more sensitive while later respond negatively to the crop yield (Figure 5.3). The marginal impact analysis of temperature reveals that the 1°C increase in temperature at germination and tillering stage leads to 0.6 percent and 0.11 percent increase in sugarcane yield, respectively.

5.2.2 Climate Change and Acreage Response Model

The fixed effect Arellano-Bond GMM estimates are used to estimate the results of equation 4.22 for acreage response of sugarcane crops in Pakistan at district level. The estimated results are given in Table 5.5. For this response estimation, linear functional form of the variables are used. The results showed that, the adjustment coefficient for area is 0.64 which is larger than the adjustment coefficient of cereal crop 0.18 calculated by Mythili, (2012b). According to the study of Surekha, (2005) that farmers are hesitant to make greater adjustments in the cereal crop. Whereas, in case of cash crops including sugarcane, farmers are readily make larger adjustments in the area. The farmers are profit maximizers and their purpose will be based on allocating additional cultivated land under cash crops.

Climate plays an important role and previous year climate influence the sugarcane farmer’s area allocation decision. Therefore, precipitation at different phenological stages of sugarcane crop were used to gauge their impacts on farmer’s future allocation of area to sugarcane crop. The results indicate that previous year precipitation at first three stages (significant at tillering stage) respond positively on future allocation of the area to sugarcane crop. Moreover, the previous year precipitation at maturity stage influence the current year acreage allocation negatively but this impact is not significant. The investment on agricultural R&D has robust negative effect on sugarcane acreage in Pakistan in major sugarcane producing districts. The results estimation shows that one million rupees increase in investment in agriculture R&D reduces the acreage allocation to sugarcane crop by 220 hectare. The reduction in the allocation of acreage in sugarcane crop may be due to reduction in the availability of the marginal land. Improved agricultural farm management practices and technological improvements reduces the area allocated to sugarcane crop and increase the farm productivity in major sugarcane producing districts of Pakistan.

Table 5.5: Result of Climate Change and Acreage Response (Arellano-Bond GMM Estimates)

Independent Variables	**Coefficient(s)**	**Independent Variables**	**Coefficient(s)**
(dependent variable)$_{-1}$	0.3576*** (0.0509)	(DAP Fertilizer Price)$_{-1}$	-0.0216*** (0.0024)
(P_G)$_{-1}$	0.2320 (0.4686)	(SOP Fertilizer Price)$_{-1}$	0.0036 (0.0033)
(P_TIL)$_{-1}$	0.6736** (0.2858)	(Cotton Yield)$_{-1}$	-0.8577*** (0.2561)
(P_GGS)$_{-1}$	0.0435 (0.2183)	(Sugarcane Yield)$_{-1}$	0.1741*** (0.0371)
(P_MS)$_{-1}$	-0.3786 (0.0074)	(Wheat Yield)$_{-1}$	-0.6636 (0.6926)
(R&D)$_{t}$	-0.2155** (0.1115)	(Maize Yield)$_{-1}$	0.0498 (0.0633)
Price of Cotton	-0.0278*** (0.0042)	Constant	-1.4024 (16.8439)
Price of Maize	-0.0030 (0.0160)	Observation	540
Price of Wheat	-0.2225* (0.1346)	Number of districts	20
Price of Sugarcane	0.1491** (0.0661)	Wald chi2(17)	756.88
(Urea Fertilizer Price)$_{-1}$	0.0825*** (0.0091)	Prob > chi2	0.0000

Standard errors in parentheses; 2. *** p<0.01, ** p<0.05, * p<0.1

Price is one of the important factor that sent strong signals to the farmers. Allocation of the area to any particular crop based on agricultural pricing policy. In Pakistan, government announces the procurement prices at the time of sowing for different crops to ensure the food security in the country. For sugarcane crop, own price and substituted crop relative price were the two important factors that contributed a lot in acreage allocation. The results confirm that own price of sugarcane has robust positive effect on sugarcane acreage. One rupees increase in sugarcane crop price per 40 kg results in additional 144 h cultivated land under sugarcane crop. Whereas, as expected the sugarcane acreage respond negatively to the relative prices of cotton and wheat crops (substituted crops). Wheat has more significant robust impacts on sugarcane acreage as compared to cotton due to its greater economic benefits and nutritional important. One rupees increased in relative procurement price of wheat per 40 kg ultimately reduces the sugarcane acreage by 223 hectares whereas cotton brings 28 hectare decline in the sugarcane acreage.

The present study used the three types of fertilizer rich in source of N, P and K namely Urea, Di-ammonium Phosphate and Sulphate of Potash, respectively. The response of the prices to acreage allocation vary with the type of the fertilizer. Urea is the most common type of fertilizer used and rich in nitrogen nutrients. Surprisingly, the current year acreage allocation shows the significant positive relation with the previous year price of urea in Pakistan. This result provides the basis that why the farmers are using more urea application for their crop. This is due to the lack of information and prevailing misperception that application of more urea fertilizer enhanced the production of the crop. Therefore, farmers didn’t response to the increase in urea prices rationally. Moreover, the previous year price of the DAP has a significant negative effect on the current year sugarcane acreage allocation. The price of the DAP fertilizer is already its peak. Thus, a slight increase in the price of the DAP results in the reduction of the future allocation of the cropland to the sugarcane crop. These prices changes will result in the imbalance use of fertilizer for crop production. Similar to the price, the previous year yield of the substituted crop has significant negative impacts on the acreage allocation of sugarcane crop. Moreover, these results are truly represent our area share findings that greater area of wheat and cotton will affect the sugarcane crop acreage allocation. However, the effect of sugarcane previous year yield affect positively and significantly to sugarcane acreage allocation in Pakistan.

5.2.2.1 Short and Long Run Elasticity

The previous studies estimate showed that sugarcane crop yield and area had short run elasticities ranging between 0.06-0.45 and 0.10-0.52, respectively. In particular, Khan and Iqbal, (1991) calculated the sugarcane crop yield and area short run elasticities are 0.52 and 0.06 respectively. However, in present study the sugarcane crop area short run elasticity is 0.11. Therefore, our results lies between the ranges of the previously conducted studies on sugarcane crop area elasticities.

Table 5.6: Elasticity of Sugarcane Crop

Crop	**Elasticity at mean**	
	Short Run	**Long Run***
Sugarcane	0.114	0.178

*LR= one minus coefficient of one-lagged dependent variable

In Table 5.6, the long run elasticity of sugarcane crop area is also reported. In the long run farmers decided to grow sugarcane crop on the basis of the yield response. The long run elasticity for area in the present study is 0.18. The long run elasticity of the sugarcane crop area is lower than the previously conducted studies including. Krishna, (1962) for India. The farmers only response to the price unless these changes were permanent and higher crop yield potentials[35].

5.2.2.2 Elasticity of Price and Non-Price Factors

The dominant factor in farmers' decision is non-price factors (Askari and Cummings, 1977b; Gulati and Kelley, 1999; Krishna, 1962; Narain, 1965). The significance of non-price factors

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[35] Please see the Table A.5 (Appendix 5) for the comparison of the different calculated elasticity

portrayed ample consideration in the literature: rainfall, irrigation, market access for both inputs and output, and literacy. The reason behind reported for a low response to prices in less developed economy is the inadequate access to input and product markets or high transaction costs associated with their use. Limited market access may be either due to physical constraints such as absence of proper road links or the distances involved between the roads and the markets, or institutional limitations like presence of intermediaries. The effect of non-price factors i.e. precipitation at crop phenological stages and investment in agricultural R&D are high as compared to the prices of the fertilizers (Table 5.7).

Table 5.7: Result of Price and Non-Price Elasticity for Sugarcane Crop at Mean

Variables	**Acreage**		**Variables**	**Acreage**	
	SR	**LR***		**SR**	**LR***
Price factors			**Non-price factors**		
Urea Fertilizer	0.522	0.334	Precipitation at germination stage	0.024	0.038
DAP Fertilizer	-0.276	-0.177	Precipitation at tillering stage	0.340	0.218
SOP Fertilizer	-0.044	-0.028	Precipitation at grand growth stage	0.064	0.041
			Precipitation at maturity stage	-0.110	-0.070
			R&D	-0.035	-0.022

*LR= one minus coefficient of one-lagged dependent variable

For sugarcane, Gulati and Kelley, (1999) estimated negative elasticities. His study directed to the inference that, own price plays a less important role in acreage decisions than non-price factors.

Similar to our study, the own price of sugarcane crop play less important role as compared to the other non-price factors-R&D, precipitation and the cross-price elasticity of the substituted crops.

5.2.2.3 Cross-Price Elasticity for Sugarcane crops

Huang and Khanna, (2010c) estimated the cross price elasticity of the different crops. According to his study, the cross price elasticity of the wheat crop with respect to corn and soybeans are 0.306 and -0.054 respectively. Our study calculate the cross price elasticity of the substituted crops (cotton, maize and wheat) with respect to sugarcane crop (Table 5.8). In absolute term, wheat has the highest cross price elasticity of area that is 0.03 but its effect is negative on sugarcane crop area. Wheat is the competing crop for sugarcane in the major sugarcane producing areas. Higher wheat procurement price attracts the farmers to allocate more area to wheat instead of sugarcane to earn higher returns. After wards, cotton has the highest area (-0.02) cross price elasticity. After the influx of Bt cotton, farmers find the new ways to earn higher return in the lesser period of crop duration. Effect of cotton price on sugarcane area is negative but this response is less elastic on sugarcane area. The cross price acreage elasticity of the sugarcane w.r.t. maize is fairly inelastic in the major sugarcane producing districts of Pakistan. These results are different from the calculated cross price elasticities in India (Mythili, 2012c). One reason for this different is the unit of the measurement because above study calculated the cross price elasticity of sugarcane in quintal but we calculated on tonnes/hectare.

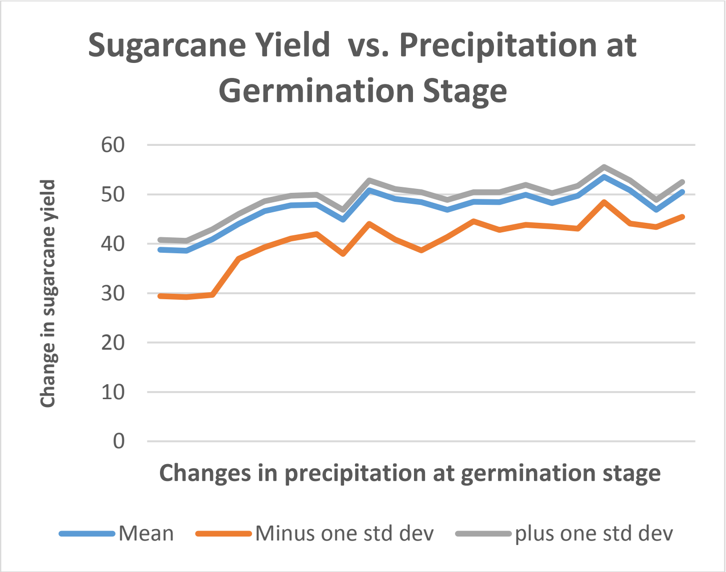
Table 5.8: Cross-Price Elasticity

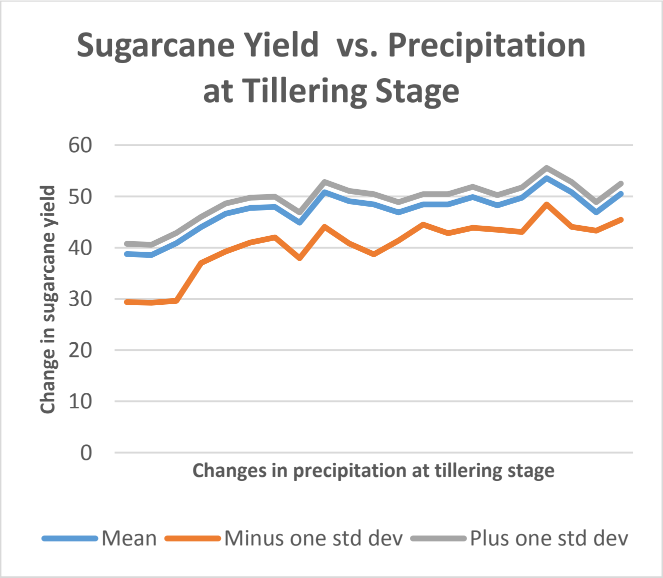
Variables	Acreage	
	SR	**LR***
Cotton	-0.015	-0.010
Maize	$-6.17\text{x}10^{-4}$	$-3.95\ \text{x}10^{-4}$
Wheat	-0.034	-0.022

*LR= one minus coefficient of one-lagged dependent variable

5.2.3 Trend in Sugarcane Yield and Precipitation

Following graphs are illustrated the overall trend in sugarcane yield change with respect to the changes in precipitation with different phenological stages of the sugarcane crop (Figure 5.4).





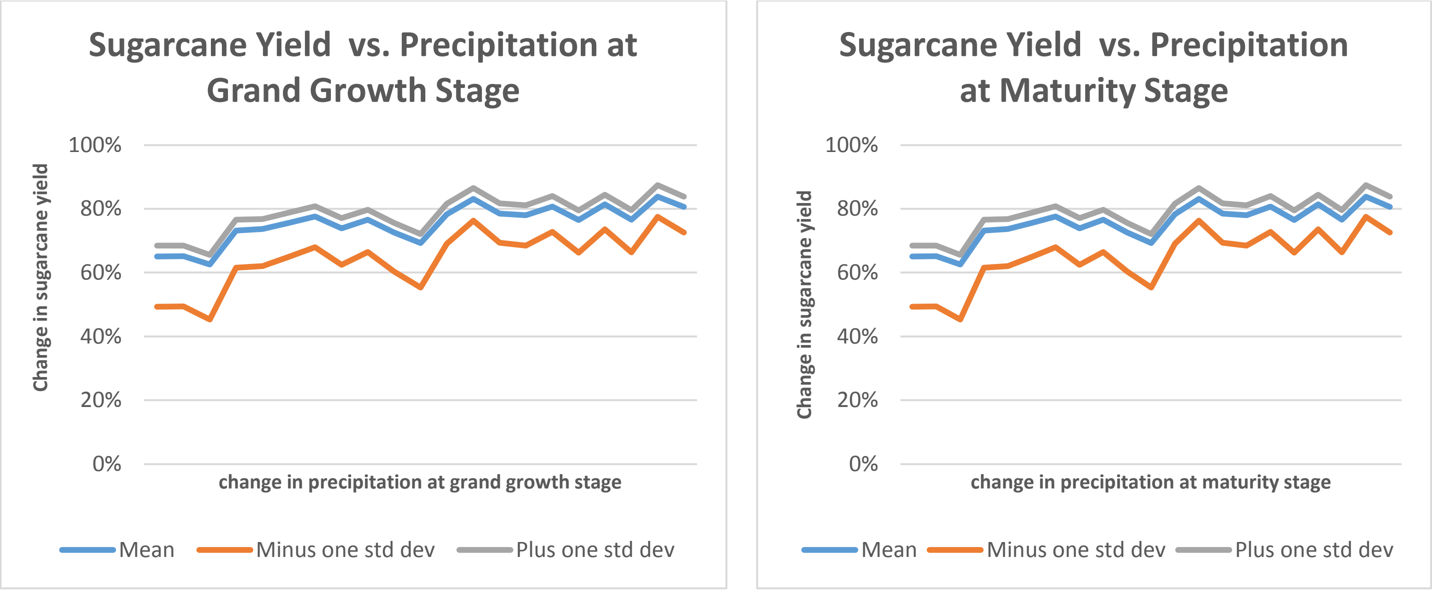
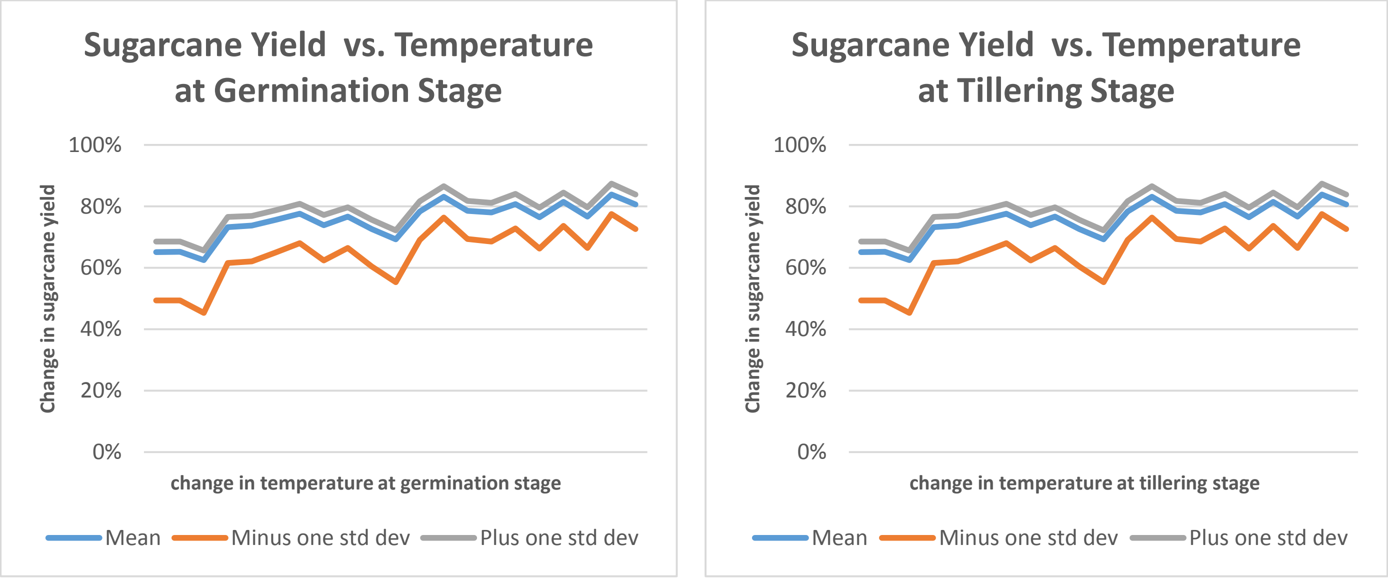


Figure 5.4 Trend in Sugarcane Yield and Precipitation

5.2.4 Trend in Sugarcane Yield and Temperature

Following graphs are illustrated the overall trend in sugarcane yield change with respect to the changes in temperature with different phonological stages of the sugarcane crop (Figure 5.5).



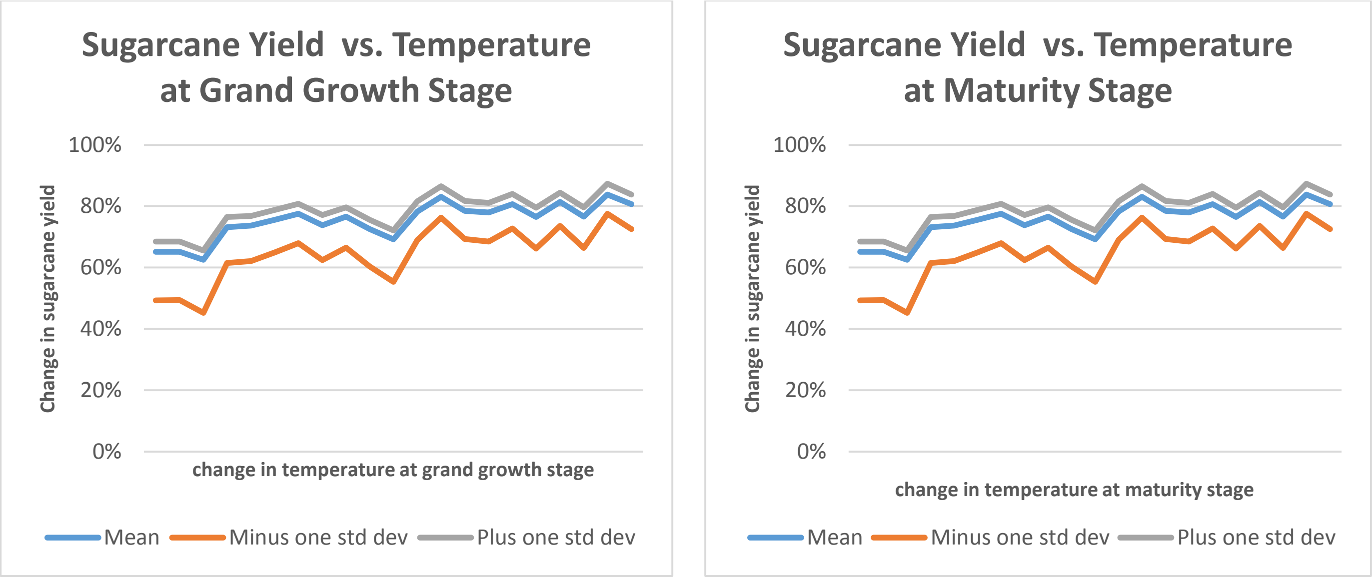


Figure 5.5 Trend in Sugarcane Yield and Temperature

5.2.5 Drought Situation in Districts of Pakistan

On the basis of the estimated results, following graph is made to illustrate the overall drought situation in Pakistan during the worst year of drought (1998-2002). Extreme drought are reported in the Rahim Yar Khan district while the normal district of the study area is the Sangher (Figure 5.6)[36].

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[36] Please see Appendix-4 for complete ranking of district from 1981-2010 according to drought index

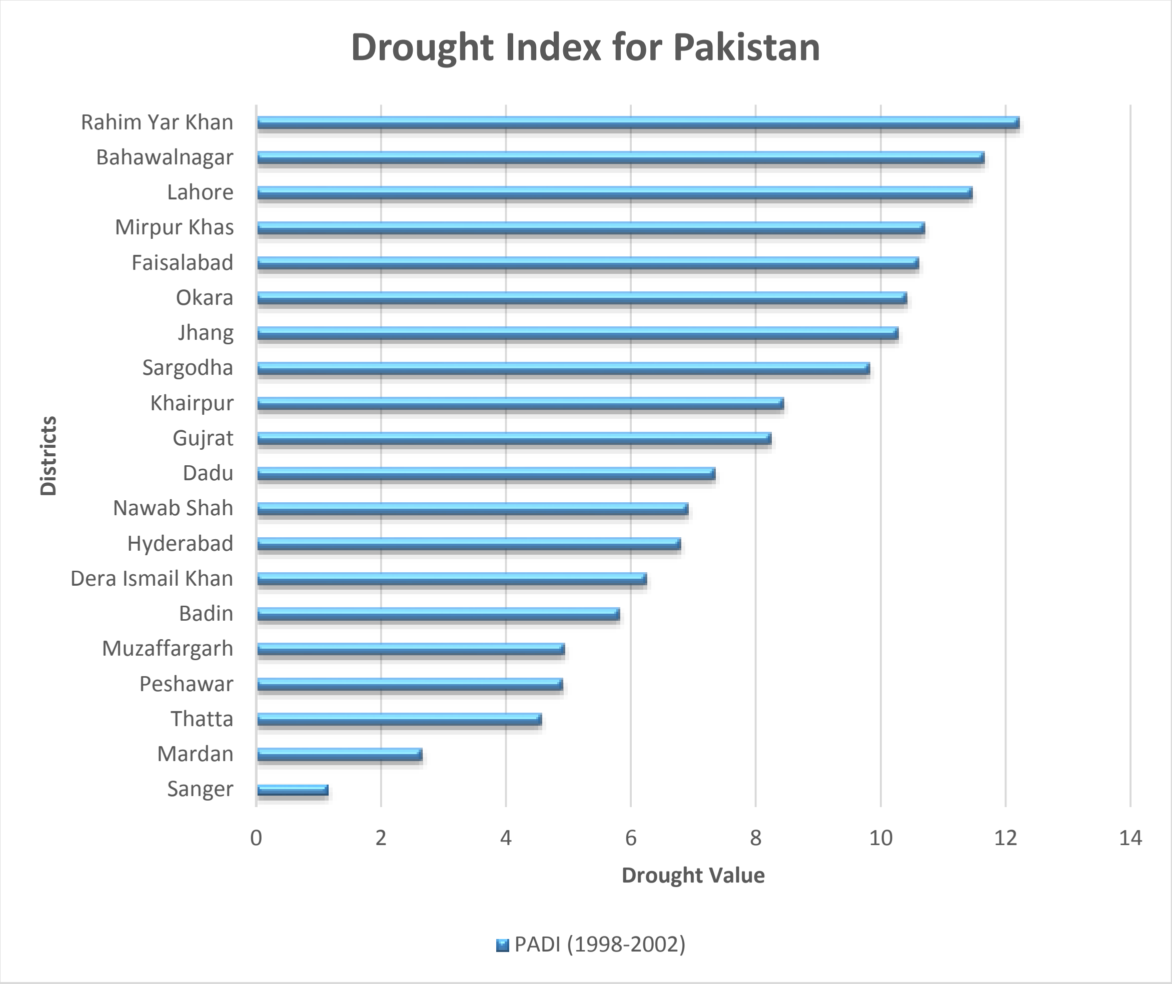

Figure 5.6 Ranking of Districts with Respect to Drought Index

Chapter 6

Conclusion and Policy Recommendations

Production of the sugarcane crop depends upon the yield and acreage response of the crop to different factors including price and non-price factors. Temperature and precipitation adversely affect the sugarcane crop but its magnitude and direction varying with different phenological stages of the crop.

Inter alia, agriculture pricing policy is the most effective tool to ensure crop production and food security in the country. Farmers received robust signals from agriculture pricing policy to adjust their area among different crops in the short run. Overall supply response of the sugarcane crop based on the yield response of the sugarcane crop in the long run. Moreover, extreme events like drought is the major environmental hurdle on the way forward to higher productivity in the sugarcane producing areas that link with temperature and precipitation also. Investments in the agricultural R&D decline the crop acreage offsetting by higher crop production with smaller plot size. Balance used of fertilizer application is needed for the sustainable crop production and ensuring food security in Pakistan. 4R strategy paved the way forward that brings prosperity for the farmers ultimately. The major source of imbalance use of fertilizer is due to lack of information and perception about the different type of fertilizers. Higher prices of DAP also badly effect the nutrients application balance for the crops.

The acreage response of sugarcane crop gives the consistent results in line with the previous research findings. In case of acreage response, the effect of previous year area, relative price of substitute crops (cotton and wheat), precipitation at tillering stage and the price of fertilizer (urea and Di-ammonium phosphate) are significant. Post green revolution era brings lot of technological improvements including better seed varieties, improved farm management practices and research and development to get rid of insect pest infestation. The results of acreage response may imply that farmers are responsive to price incentive but it takes time due to infrastructural problems. Agriculture support price policy will be effective if farmers believes that these prices are permanent. Therefore, it can be determined that sugarcane market price policies and market mediations are on their own inadequate to stimulus land allocation in the case of sugarcane.

In order to enhance sugarcane productivity and production, government policy of de-regulation for inorganic fertilizer to provide input at lower cost for the poor farmers should start. There should be an essential for ample public investments in rural infrastructure and efficient facilities that facilitate fertilizer trade as well as enhance access by sugarcane farmers to inorganic fertilizer. There should be the consistent allocation of the agricultural R&D funds specific to the area which gives highest production of sugarcane crop. Policy should also work towards developing improved drought resistant and heat resistant sugarcane varieties. Finally there is a need for extension and agricultural advisory service providers to work with sugarcane crop growers to enhance labor management skills and promote 4R strategy nutrient stewardship framework. This can be accomplished via capacity building efforts that pivot on farm business management skills and efficient allocation of available resources.

6.1 Limitation of Study

There are various type of limitations confronting during this district level study. These are

- Availability of district level data of labour engage in agriculture crop sector. Labour is an important variable in the production process. Therefore, the effect of labour comes under the error term in this study.
- Availability of district level soil fertility data in Pakistan
- Frost is an important climatic factor that influenced the sugar quality, seed quality (reduced germination), plant and leaf growth. There is no such data available at district level.

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Appendices

Appendix 1:

Table A.1: List of Districts

Serial No.	Districts	Province
1	Badin	Sindh
2	Dadu	Sindh
3	Hyderabad	Sindh
4	Khairpur	Sindh
5	Mirpur Khas	Sindh
6	Nawab Shah	Sindh
7	Sangher	Sindh
8	Thatta	Sindh
9	Bahawalnagar	Punjab
10	Faisalabad	Punjab
11	Gujrat	Punjab
12	Jhang	Punjab
13	Lahore	Punjab
14	Muzaffargarh	Punjab
15	Okara	Punjab
16	Rahim Yar Khan	Punjab
17	Sargodha	Punjab
18	Dera Ismail Khan	KPK
19	Mardan	KPK
20	Peshawar	KPK

Appendix 2:

Table A.2: Weight Factors

Month	Weight Factors (w_i)
October	0.1
November, December	0.4
January-April	0.5
May	0.8
June	1.2
July	1.6
August	0.9
September	0.1

Source: Palfai and Herceg, (2011)

Appendix 3:

Table A.3: Drought Categories

PaDI (°C/100 mm)	Description
< 4	Drought less Year
4 –6	Mild Drought
6 –8	Moderate Drought
8 –10	Heavy Drought
10 –15	Serious Drought
15 –30	Very Serious Drought
> 30	Extreme Drought

Source: Palfai and Herceg, (2011)

Appendix 4:

Table A.4 District Drought Situation

Districts	PADI	Classification
Sindh	**6.74**	Moderate Drought
Sanger	1.98	Drought less Year
Thatta	4.26	Mild Drought
Badin	7.77	Moderate Drought
Hyderabad	7.13	Moderate Drought
Nawab Shah	5.34	Mild Drought
Dadu	4.75	Mild Drought
Khairpur	6.64	Moderate Drought
Mirpur Khas	16.06	Very Serious Drought
KPK	**4.83**	Mild Drought
Mardan	3.23	Drought less Year
Peshawar	4.68	Mild Drought
Dera Ismail Khan	6.59	Moderate Drought
Punjab	**11.02**	Serious Drought
Muzaffargarh	6.99	Moderate Drought
Gujrat	9.40	Heavy Drought
Sargodha	9.49	Heavy Drought
Jhang	10.81	Serious Drought
Okara	11.43	Serious Drought
Faisalabad	10.19	Serious Drought
Lahore	10.25	Serious Drought
Bahawalnagar	14.01	Serious Drought
Rahim Yar Khan	16.59	Very Serious Drought

Source: Author’s own calculation

Appendix 5:

Table A.5: Details of the Variables

Variable	**Details**	**Variables**	**Details**
ln(y)	Log of yield	P_G^2	Square of Precipitation at germination stage
P_G	Precipitation at germination stage	P_TIL^2	Square of Precipitation at tillering stage
P_TIL	Precipitation at tillering stage	P_GGS^2	Square of Precipitation at grand growth stage
P_GGS	Precipitation at grand growth stage	P_MS^2	Square of Precipitation at maturity stage
P_MS	Precipitation at maturity stage	T_G^2	Square of Temperature at germination stage
T_G	Temperature at germination stage	T_TIL^2	Square of Temperature at tillering stage
T_TIL	Temperature at tillering stage	T_GGS^2	Square of Temperature at grand growth stage
T_GGS	Temperature at grand growth stage	T_MS^2	Square of Temperature at maturity stage
T_MS	Temperature at maturity stage	P*T_G	Precipitation*temperature at germination stage
DV_PG	Shocks in precipitation at germination stage	P*T_TILL	Precipitation*temperature at tillering stage
DV_PTIL	Shocks in precipitation at tillering stage	P*T_GGS	Precipitation*temperature at grand growth stage
DV_PGGS	Shocks in precipitation at grand growth stage	P*T_MS	Precipitation*temperature at maturity phase
DV_PMS	Shocks in precipitation at maturity stage	PADI	Palfai Drought Index

Variable	**Details**	**Variables**	**Details**
DV_TG	Shocks in temperature at germination stage	ln(A)	Log of sugarcane cropped area
DV_TTIL	Shocks in temperature at tillering stage	IA	Proportion of irrigated acres to cultivated acres
DV_TGGS	Shocks in temperature at grand growth stage	ln(FN)	Log of fertilizer (NPK) nutrients uptake
DV_TMS	Shocks in temperature at maturity stage	ln(R&D)	8 Years average of R&D expenditure
ln(NT)	Log of total number of tractors	PFR	Ratio of phosphorus nutrients to total NPK nutrients uptake

Appendix 6:

Table A.6: Comparison of Own-Price Elasticity

Study		**Period**	**Acreage**	
			SR	LR*
Krishna (1962)		1913-46	0.17	0.30
Ashiq (1981)		1957-80	0.45	3.75
Tweeten (1986)		1962-83	0.36	0.70
Khan and Iqbal (1991)		1956-87	0.06	0.47
Mushtaq (2002)		1960-96	0.15	0.58
Mohammad (2005)	Cotton Zone	1970-2001	0.15	0.49
	Rice Zone		0.17	0.58
	Mixed Zone		0.22	0.62
Mythili (2012)	Pre-reform	1970-2005	0.267	1.510
	Post-reform	1970-2005	0.268	1.514
Our study		1981-2010	0.114	0.178

Appendix 7:

Low rainfall over longer period of time is characterize as drought in any particular area. There is a need to quantify the factors that can contribute in drought. Table A.7 reveals that 1 mm increase in precipitation in the districts of Pakistan will reduce the drought by 0.048 (°C/100mm) and vice versa. The major reason behind the persistent severe drought is the increasing temperature trend in districts of Pakistan. 1°C increase in the temperature results in the 11.61 (°C/100mm) in the Palmer Drought Index. These results are different with the finding of the Lee and Nadolnyak, (2012).

Table A.7 Determinants of Drought

Independent Variable	**Coefficient**
Precipitation	-0.0478** (0.0217)
Temperature	11.6110** (4.9159)
Constant	287.3607*** (126.8968)

Source: Author's own calculation