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RESEARCH ARTICLE

The combined effect of climatic factors and technical advancement on yield of sugarcane by using ARDL approach: evidence from Pakistan

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Abstract
Sugarcane is one of the most important crops in the world and has a major influence on environmental concerns. This study aims to examine the association between sugarcane crop yield, climate change factors, and technical advancement using time series data for the period of 1989 to 2015 in Pakistan. An autoregressive distributed lag (ARDL) model and descriptive statistics analysis were employed in this study. The outcomes of the bound *F*-test for co-integration confirmed that there is a long-run and short-run equilibrium among sugarcane crop yield, temperature, rainfall, fertilizer use, and agricultural machinery. The results of long-run estimate that the coefficient of area, rainfall, and fertilizer use have significantly positive impacts on sugarcane crop yield. The coefficient of temperature had positive and non-significant while agricultural machinery had negative and statistically significant relationship with sugarcane crop yield. In the short-run estimates, the coefficient of area, rainfall, and fertilizer use have statistically positive impact, temperature had non-significant impact, and agricultural machinery had significantly negative impact on the yield of sugarcane crop. In addition, both CUSUM and CUSUMsq test results confirmed the goodness of fit of this model. The outcomes of our study suggest that climate change has negative impact on the yield of sugarcane. Based on the study findings, the Government requires to take effective measures for constructive policy-making and identification of environmental threats in Pakistan. Large-scale mechanical activities and rapid growing may be useful initiatives for raising the yield of sugarcane. Furthermore, technical advancement needs to be improved because it plays a vital role in increasing the yield of sugarcane and other major crops.

Keywords Sugarcane crop · Climate change · Fertilizer · Agricultural machinery · ARDL model · Pakistan

Introduction

Climate change is becoming a serious threat for the global food security. The concept is becoming burdensome on the natural and human capital and therefore a major challenge to the social, economic, and ecological sustainability of the resources stricken developing regions such as South Asia (Bokhari et al. 2018; IPCC 2014, 2018). The researchers such as Abid et al. (2016), Atif et al. (2018), and Woods et al. (2017) opined that the consequential impacts of these weather and climatic fluctuations are adversely influencing the environmental resources of these regions. Whereas the economic and social viabilities of these contextual settings depend on the agricultural productivities, therefore, integrated efforts are incumbent for ensuring the resilience of their agro-based economies. Currently, numerous countries around the globe are vulnerable to climate change and Pakistan is one of among those countries. Very hot summer and very cold winter prevail

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in the country. Meteorological variables monitor the availability of resources and regulate the basic growth processes required. That is why agriculture is highly vulnerable to climate change. Although, the phenomenon and patterns behind this fact are uncertain as well as not known clearly (Tao et al. 2014; Tao and Zhang 2013; Wilcox and Makowski 2014).

Sugarcane is currently one of the most promising bioenergy crop for reducing crude oil dependency and mitigating greenhouse gas (GHG) emissions (Jaiswal et al. 2017), especially by its rapid growth, high yield, and improved energy balance (energy delivered per energy spent) (Muñoz et al. 2014) (Fig. 1). The countries with the largest sugarcane production volume in 2019 were as follows: Brazil (45.67% of world production), India (24.49%), Thailand (7.95%), China (6.67%), and Pakistan (4.06%) (FAO 2019). In order to achieve maximum sugarcane production, large quantities of water are required, with an annual water requirement from 1400 mm to more than 2000 mm in some regions (Brauman and Viart 2016). This condition may result in environmental concerns about water scarcity (Scarpare et al. 2016), particularly with regard to the expansion of sugarcane in countries where its cultivation depends on irrigation (Martin et al. 2007). It is also important to improve the efficiency of agricultural activities because the productivity of high-water-requirement crops such as sugarcane can only be sustained by improving the efficiency of irrigation water (Singh et al. 2018).

On the other hand, socioeconomics is based on data regarding the statistics by implementing the empirical formula such as regression and panel data models (Conradt et al. 2016; FAO 2016; Webb et al. 2008a, b) as well as economic models such as Ricardian models and yield function. The major advantages of such socio-economic data are their open valuation of uncertainties and their lesser dependency on data regarding field experiments. Because of these beneficial outcomes, such kind of models are considered as substitute to process based models (Lobell and Burke 2010). It is surprising that there very brief empirical quantitative analysis regarding the effects of climate change and improvement in agricultural technology on crop production and yield. Particularly, there are various uncertainties concerning the impact of climate change and the development of agricultural technologies on crop production capability and on active mechanisms or driving factors (Tao and Zhang 2013; Zhang and Huang 2013). The reported maximum temperature can be used to calculate the influence of climate, because maximum temperature is an important factor due to its role in the functionalities of crops including development and growth. Though many crops have rapid growth rate at high temperature, their production can be decreased, if their maximum growth rate is not complemented with fertigation and irrigation (USGCRP 2009).

Another important climatic variable is rainfall which influences the agricultural production. As water plays a crucial role on the crop's life, so rainfall has a valuable part in agriculture sector. Every year, Indus basin area of Pakistan receives 40 million acre feet of water from rainfall. Monsoons and western aggravations are two primary wellsprings of precipitation in Pakistan, and it has been reported that about 70% of annual rainstorm precipitation occurs between July and September (Ahmed et al. 2007). Due to the expansion of arable land, about 20% of the increases in production will arise by 2050 (Bruinsma 2009). However, research has shown that if the climate of two regions is comparable, still the agricultural productivity may differ substantially. This is due to difference in agricultural mechanization, technology, and use of various inputs such as seed and fertilizer. For example, the average

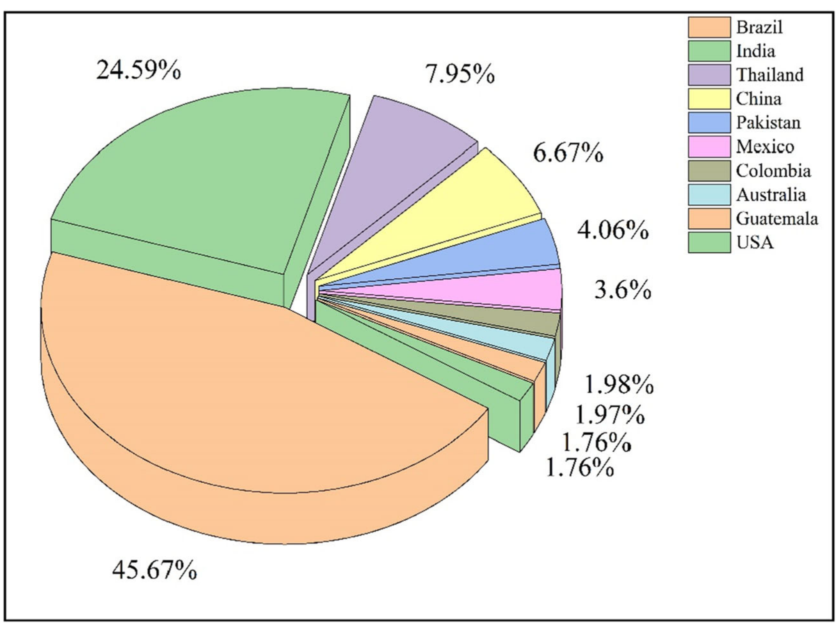


Fig. 1 Percentage of sugarcane crop area harvested. Source: FAO (2019)

yield in EU is 5 tons per hectare, 3 tons per hectare in developing world, and only 1.2 tons per hectare in SSA (FAO 2013).

Similarly, another important factor is fertilizer, which is a natural of chemical substance used for the preparation of agricultural land to boost up its fertility. Mixture of carbon, hydrogen, and oxygen is the most important type of fertilizers. If the same part of land is cropped frequently over the years, then it results in the infertility and low production of crops. In Pakistan, fertilizer consumption was 4089.1 thousand nutrient tons and containing 2803.9 thousand nutrient tons being covered in the Punjab region (National Fertilizer Development Center 2014). Recognition of unpremeditated active factors responsible for improving sugarcane yield is necessary for the betterment of predictions about the impact of climate change and advanced agricultural technology on crop productivity. It will also help to improve well-established agricultural adaptation strategies in the future. Autoregressive distributed lag (ARDL) model helps to know about the existence of long-run relationships among several variables (Pesaran and Shin 1998). The key advantage of this model that differentiates it from other methodologies is that it can detect long-run or short-run association between variables. Another feature of ARDL model is that it can be employed for the small data and order of variable integration is not necessary. Therefore, recent study applied ARDL model for the identification of the relationship between sugarcane crop yield, climate change, and technical advancement on historical data from 1989 to 2015. The rest of the study is developed as follows: the second segment is review of literature on the relationship among the crops yield, climate change, and technical advancement. The third segment shows the materials and methods which include study area, data sources and description, and model specification. The fourth segment summarizes the findings and discussions consisting of descriptive statistics, unit root measures, ARDL bound tests, analysis of long-run and short-run estimates, and diagnostic tests. The fifth segment is conclusion of the study.

Literature review

Agriculture is the most vulnerable economic sector through such changes, and for the past 30 years, numerous studies have attempted to estimate the effect of changing climate on crop yields and their production (Adams et al. 1990; Attavanich and McCarl 2013; Mendelsohn et al. 1994; Miao et al. 2015; Parry et al. 2004; Schlenker and Robert 2009). It has been speculated that increase in the concentration of CO_2 and emission of other greenhouse gases results in an increase in temperature and alteration of precipitation patterns (IPCC 2007). Agriculture sector is much sensitive and highly influenced by climate change. Wheat is main crop in many regions of the world such as Asia, Europe, and Northern Africa. Therefore, several studies have identified the connectivity of climate change and crop yield (Gömann 2015; Özdoğan 2011; Potgieter et al. 2013; Tao et al. 2006, 2008, 2012; Webb et al. 2008a, b; You et al. 2009).

Regardless of the fact that Pakistan has been a low producer of CO_2 gasses (0.2 million metric tons), it is rated as one of the worst affected countries by global warming; however, Pakistan has not taken any effective measures to address this issue (Smadja et al. 2015). This incur enormous costs resulting from damage to property and infrastructure, reduction in agricultural productivity, and rehabilitation cost of areas severely affected by natural disasters as a result of the frequent climate events. Due to the rise in temperature, rainfall will also decrease which affects crop production. If there is a decrease in rainfall by 6%, the country's net irrigation water supplies could increase by nearly 29%. The increase in temperature and decrease in rainfall are likely to have adverse consequences over 1.3 million small farm households in Pakistan and the crops production consisting cereals, fruits, and vegetables.

Climate change can directly affect crops through rising temperature and changing rainfall patterns or indirectly affect crops through soil, nutrient, and increasing pests interference (Rosenzweig et al. 2001). Although the world may be able to cope with food insecurity at the macro level, the problem may also exist at the micro level with the shortage of food in developing countries compensated by developed countries receiving the benefits from climate change (Parry et al. 2004). Previous studies also revealed that climate change is projected to negatively affect the global food system and food supply may not be available to meet demand in the future (Attavanich and McCarl 2013; Brown et al. 2017). The variations in environment influence the production of agriculture sector by shift in global temperatures, fluctuations in rainfall, and other similar factors. People in the south will suffer the most due to expected decline in crop yields, while people in the North may get benefits from higher temperatures. It is projected that between 2080 and 2100, about 15–30% of agriculture output would be adversely affected (FAO 2013). Further reduction in crop yield may result in Africa, Latin America, and Asia unless appropriate adaptation measures are not taken. A previous study by Boko et al. (2007) estimated that it would cost about 5–10% of GDP for Africa to take adaptation steps to tackle climate change. Furthermore, they predicted that about 50% of decline in agricultural crops would be witnessed by 2020 and the crop revenue may possibly further decline even up to 90% by 2100. The shift in the patterns of rainfall has already influenced more than one billion people in South Asia (Turner and Annamalai 2012).

In China, the research work on climate change impact on growth and yield has mostly overlapped (Tao et al. 2006, 2008, 2014). For the estimation of major effects of climate

Table 1 Descriptive statistics of all the variables for sugarcane crop

Variables	Yield (kg/ha)	Area (hectare)	Mean temperature (°C)	Rainfall (mm)	Fertilizer (10^4t)	Total machinery (10^3kw)
Mean	48,7105.9	1,009,057.0	19.90096	27.42422	2987.858	23,884.00
Median	48,0560.0	999,700.0	19.88572	26.84747	2964.000	23,482.75
Maximum	57,8974.4	1,241,300.0	20.71786	46.58511	4360.000	34,357.09
Minimum	40,7204.0	854,300.0	18.98928	13.17074	1790.168	13,994.00
Std. Dev.	49,381.37	100,380.6	0.428638	9.790062	783.0331	6285.724
Skewness	0.297427	0.468685	0.009124	0.561099	− 0.038813	− 0.083604
Kurtosis	2.167847	2.503216	2.266404	2.458054	1.725155	1.869074
Jarque-Bera	1.177123	1.266139	0.605807	1.747163	1.835163	1.470320
Probability	0.555125	0.530959	0.738670	0.417454	0.399484	0.479429

Source: Author's formation

change on yield and growth, two methods are generally implemented in the field of natural science: discovering the effects of long-term variation of (1) crop simulation models (El Chami and Daccache 2015; Li et al. 2015) and the scenarios regarding the climate change (2) implementing the experiments related to artificial climate chamber (Jalota et al. 2014; Özdoğan 2011; Wilcox and Makowski 2014). Parameters have unknown values that might be responsible for the uncertain estimation of model projections (Lobell and Burke 2010). Prediction in risk becomes evident because of poor understanding of growth mechanisms and processes. Instead of other approaches, more time and additional budget are required for field experiments but the findings are frequently forthright (Guo 2015).

In China, the upgradation of mechanical technology, chemical fertilizers, and technology regarding the crop cultivation is swift and helps to increase crop production and yield. Apart from these facts, advancement and implementation of large machinery for the agriculture as well as amenities concerning the water conservation have played a crucial role for improved wheat yield (Guo et al. 2014, 2015; Xiangxiang et al. 2013). Tremendous research has been undertaken to elaborate the response mechanisms of crop growth and yield because of change in climate. Such researches implemented the various crop models and states regarding climate change (Duan 2011; Li et al. 2015) and by applying the statistical analysis depending on the historical data from several experimental areas (Gornott and Wechsung 2016; Siddiqui et al. 2012) or responses due to developments in agricultural technology (Duan 2011; Tian and Wan 2000).

Materials and methods

Study area

Pakistan is located in South Asia, where the geographical location, high population, and less technical resource base made this country extremely vulnerable to climate change. The agriculture sector is the backbone of Pakistan's economy because it contributes to the total income of the country. The agriculture sector assists the 42.3% of rural citizen's as livelihood source and contributes 19.8% to the gross domestic product (GDP) of the country. The worst countries facing food insecurity contain a lot of Asian and African countries, most of which are not capable of taking useful measures to overcome this disastrous problem. Pakistan is listed among the countries where almost 65% of the world's inhabitants live and is facing the difficulties of food shortage problems. The listed countries are China, Indonesia, India, Bangladesh, Congo, Pakistan, and Ethiopia (FAO 2013).

Data sources and description

Climatic variables (mean temperature and rainfall) data were collected from Pakistan Meteorological Department, while the fertilizer use and agricultural machinery use data were gathered from Pakistan Survey Report 2017/16 2016/2017. In this study, we examine two types of factors which influence yield per unit area. The first one is the climatic change factors, which consist of mean temperature and rainfall. Average mean temperature is taken as temperature for selected crop (sugarcane) in growth stages, while average rainfall is the total rainfall for sugarcane crop in growth stages. The second one factor is the technical advancement factors, which consist of fertilizer use, how much agricultural machinery is used, and the cultivation area for sugarcane crop. Secondary data for all the time period 1989–2015 were collected about all variables.

In our study, we took six different variables and applied a model which give us the relationship among the selected crop (sugarcane) yield and the climatic factors and technological advancement factors:

Y: yield of the study crop (sugarcane) in kilogram per acre
A: area for the selected study crop cultivation in thousands of hectares

T: mean temperature for the study crop (sugarcane) in degree Celsius

R: total rainfall for the study crop (sugarcane) taken in millimeters

F: fertilizer used in millions of tons

M: agricultural machinery used in units of ten thousand kilowatts

In this study, the sugarcane crop yield per unit area or Y was used as the dependent variable in model, while the remaining variables A, T, R, F, and M were all considered as independent variable in the model. Table 1 shows the descriptive statistics of the variables for sugarcane crop.

Data analysis and model specification

This study uses autoregressive distributed lag (ARDL) bound technique proposed by Pesaran et al. (2001) for the reason that this technique is used to evaluate the equations when the variables are stationary at a level $I(0)$ and also in first difference $I(1)$ (Asumadu-Sarkodie and Owusu 2016; Danish et al. 2018; Rahman and Kashem 2017; Shahbaz et al. 2013). A spurious regression may arise when we have time series data. Co-integration test was developed and employed to find out a long-run relationship among time series variables from avoiding a spurious regression (Nkoro and Uko 2016). According to Engle and Granger (1987), the co-integration is like this, if we have two or more than two integrated individual series, but some of these linear combinations have a integration in lower order, then this types of series are called co-integrated. We employed ARDL model in this study, to explore the long-run relationship among the variables being modeled.

The ARDL model is used in this research work because this model has several advantages. (a) If we have small sample size, then ARDL model is best to use, (b) another advantage of ARDL model is that it is suitable or applied either the variables were stationary in their level form ($I(0)$) position or the variables were integrated at first order and stationary in their difference ($I(1)$) or combination of both $I(0)$ and $I(1)$. (c) ARDL model can be used to calculate long-run and short-run coefficients at the same time. The short-run coefficients reflect the association between the deviations of the dependent variable from its long-run tendency. Notably, the ARDL approach comprises the bias-corrected bootstrap technique and non-linear functions of the coefficients of the conditional error correction model, which can be used for the estimation of predictable statistical implications for the long-run association between variables. The relationship among the sugarcane crop yield and the independent variables was constructed as below:

$$Y_t = \int(A, T, R, F, M) \quad (1)$$

Now first of all, we transformed all the study variables into natural logarithmic form. The admirable form of the equation was exhibited as follows:

$$\ln Y_t = \beta_0 + \beta_1 \ln A_t + \beta_2 \ln T_t + \beta_3 \ln R_t + \beta_4 \ln F_t + \beta_5 \ln M_t + \varepsilon t \quad (2)$$

In our study, we focused on the long-run and short-run relationship between chosen variables from 1989 to 2015, so for that reason, the ARDL model does not include year term. The ARDL model was formulated as follows:

$$\begin{aligned}\Delta \ln Y_t = {} & \beta_0 + \sum_{i=1}^{k} \beta_1 \Delta \ln Y_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln A_{t-i} \\ & + \sum_{i=1}^{k} \beta_3 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln R_{t-i} + \sum_{i=1}^{k} \beta_5 \Delta \ln F_{t-i} \\ & + \sum_{i=1}^{k} \beta_6 \Delta \ln M_{t-i} + \gamma_1 \Delta \ln Y_{t-i} + \gamma_2 \Delta \ln A_{t-i} \\ & + \gamma_3 \Delta \ln T_{t-i} + \gamma_4 \Delta \ln R_{t-i} + \gamma_5 \Delta \ln F_{t-i} \\ & + \gamma_6 \Delta \ln M_{t-i} + \varepsilon_t \end{aligned} \quad (3)$$

$$\begin{aligned}\Delta \ln A_t = {} & \beta_0 + \sum_{i=1}^{k} \beta_1 \Delta \ln A_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln Y_{t-i} \\ & + \sum_{i=1}^{k} \beta_3 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln R_{t-i} + \sum_{i=1}^{k} \beta_5 \Delta \ln F_{t-i} \\ & + \sum_{i=1}^{k} \beta_6 \Delta \ln M_{t-i} + \gamma_1 \Delta \ln A_{t-i} + \gamma_2 \Delta \ln Y_{t-i} \\ & + \gamma_3 \Delta \ln T_{t-i} + \gamma_4 \Delta \ln R_{t-i} + \gamma_5 \Delta \ln F_{t-i} \\ & + \gamma_6 \Delta lnM_{t-i} + \varepsilon_t \end{aligned} \quad (4)$$

$$\begin{aligned}\Delta \ln T_t = {} & \beta_0 + \sum_{i=1}^{k} \beta_1 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln A_{t-i} \\ & + \sum_{i=1}^{k} \beta_3 \Delta \ln Y_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln R_{t-i} + \sum_{i=1}^{k} \beta_5 \Delta \ln F_{t-i} \\ & + \sum_{i=1}^{k} \beta_6 \Delta \ln M_{t-i} + \gamma_1 \Delta \ln T_{t-i} + \gamma_2 \Delta \ln A_{t-i} \\ & + \gamma_3 \Delta \ln Y_{t-i} + \gamma_4 \Delta \ln R_{t-i} + \gamma_5 \Delta \ln F_{t-i} \\ & + \gamma_6 \Delta \ln M_{t-i} + \varepsilon_t \end{aligned} \quad (5)$$

$$\begin{aligned}\Delta \ln R_t = {} & \beta_0 + \sum_{i=1}^{k} \beta_1 \Delta \ln R_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln A_{t-i} \\ & + \sum_{i=1}^{k} \beta_3 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln Y_{t-i} + \sum_{i=1}^{k} \beta_5 \Delta \ln F_{t-i} \\ & + \sum_{i=1}^{k} \beta_6 \Delta \ln M_{t-i} + \gamma_1 \Delta \ln R_{t-i} + \gamma_2 \Delta \ln A_{t-i} \\ & + \gamma_3 \Delta \ln T_{t-i} + \gamma_4 \Delta \ln Y_{t-i} + \gamma_5 \Delta \ln F_{t-i} \\ & + \gamma_6 \Delta \ln M_{t-i} + \varepsilon_t \end{aligned} \quad (6)$$

Table 2 Correlation matrix results

Variables	Yield	Area	Mean temperature	Rainfall	Fertilizer	Total machinery
Yield	1					
Area	0.676806	1				
Mean temperature	− 0.119508	− 0.043226	1			
Rainfall	0.635425	0.304558	− 0.532792	1		
Fertilizer	0.824587	0.488847	0.0687156	0.391661	1	
Total machinery	0.0070337	0.066585	− 0.303784	0.166145	0.064355	1

$$\begin{aligned}\Delta \ln F_t = \beta_0 &+ \sum_{i=1}^{k} \beta_1 \Delta \ln F_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln A_{t-i} \\ &+ \sum_{i=1}^{k} \beta_3 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln R_{t-i} + \sum_{i=1}^{k} \beta_5 \Delta \ln Y_{t-i} \\ &+ \sum_{i=1}^{k} \beta_6 \Delta \ln M_{t-i} + \gamma_1 \Delta \ln F_{t-i} + \gamma_2 \Delta \ln A_{t-i} \\ &+ \gamma_3 \Delta \ln T_{t-i} + \gamma_4 \Delta \ln R_{t-i} + \gamma_5 \Delta \ln Y_{t-i} \\ &+ \gamma_6 \Delta \ln M_{t-i} + \varepsilon_t \end{aligned} \quad (7)$$

$$\begin{aligned}\Delta \ln M_t = \beta_0 &+ \sum_{i=1}^{k} \beta_1 \Delta \ln M_{t-i} + \sum_{i=1}^{k} \beta_2 \Delta \ln A_{t-i} \\ &+ \sum_{i=1}^{k} \beta_3 \Delta \ln T_{t-i} + \sum_{i=1}^{k} \beta_4 \Delta \ln R_{t-i} \\ &+ \sum_{i=1}^{k} \beta_5 \Delta \ln F_{t-i} + \sum_{i=1}^{k} \beta_6 \Delta \ln Y_{t-i} + \gamma_1 \Delta \ln M_{t-i} \\ &+ \gamma_2 \Delta \ln A_{t-i} + \gamma_3 \Delta \ln T_{t-i} + \gamma_4 \Delta \ln R_{t-i} \\ &+ \gamma_5 \Delta \ln F_{t-i} + \gamma_6 \Delta \ln Y_{t-i} + \varepsilon_t \end{aligned} \quad (8)$$

Now to estimate the long-run association among variables, the error correction model (ECM) can be determined. The above equations will changed to the general ECM equation which is given below:

$$\begin{aligned}\Delta \ln Y_t = \lambda_0 &+ \lambda_{1i} \sum_{i=1}^{k} \Delta \ln Y_{t-i} + \lambda_{2j} \sum_{j=1}^{k} \Delta \ln A_{t-i} \\ &+ \lambda_{3k} \sum_{k=1}^{k} \Delta \ln T_{t-i} + \lambda_{4l} \sum_{l=1}^{k} \Delta \ln R_{t-i} \\ &+ \lambda_{5m} \sum_{m=1}^{k} \Delta \ln F_{t-i} + \lambda_{6n} \sum_{n=1}^{k} \Delta \ln M_{t-i} \\ &+ \varphi \mathrm{ECM}_{t-i} + \varepsilon_t \end{aligned} \quad (9)$$

where λ_0 is a drift component, Δ is the first-difference operator, and ε_t is a white noise term. Error correction dynamics used in the above Eq. 9 are the terms with summation signs. The coefficients λ_{1i}, λ_{2j}, λ_{3k}, λ_{4l}, λ_{5m}, and λ_{6n} indicate the short-run dynamics of the model while β_1, β_2, β_3, β_4, β_5, and β_6 are the long-run coefficient, which represent the long-run relationship among the variables.

Now we will run the autoregressive distributed lag (ARDL) bound testing approach to estimate the co-integration (long-run) relationship among the study variables. Ordinary least square (OLS) is computed to find out either co-integration exists or not. Then, an F-test is performed to check the hypothesis of no co-integration between the variables. The null hypothesis of no co-integration or no long-run relationship among the yield per unit area, area for cultivation, mean temperature, rainfall, fertilizer use, and agricultural machinery were given as follows:

$$H_0: \quad \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$$

The alternative hypothesis estimates the long-run relationship, or co-integration among the variables is given as follows:

$$H_0: \quad \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 = 0$$

To test the existence of a long-run relationship among the variables, the F-statistics is performed. If the F-statistics value falls above the upper bound critical value, then the null of no co-integration is rejected. However, if the computed F-statistics falls within the critical value band, then the results would be inconclusive. Finally, if the F-statistics value falls below the lower bound value, then the null hypothesis is accepted.

Results and discussion

Descriptive statistics

The descriptive statistics are reported in Table 1, to calculate the basic properties of all the study variables. During the sugarcane crop growth stage, the minimum average temperature was 18.9 °C while the maximum average temperature was 20.7 °C, respectively. Table 1 displays us that there is a large variation in the sugarcane yield per unit area from 1989 to 2015. For instance, the sugarcane minimum yield is reported as 40,381.37 kg/ha, while sugarcane maximum yield is calculated as 578,974.4 kg/ha. Correlation analysis is quantified in

Table 2 for all study variables, to find out the interconnected relationship of one variable with another.

Figure 2 shows that the sugarcane yield per unit area sharply increased from 1989 to 2015. The outcome displays in Fig. 2 shows that there is an increase in the annual area of sugarcane production during the study period. There is a gradual increase in the average mean temperature for sugarcane growth period from 1989 to 2015 (Fig. 2). The total rainfall also shows great fluctuation in sugarcane crop growth period. We also calculate that the fertilizer uses from 1989 to 2015 in Fig. 5. The fertilizer uses and the total agricultural machinery uses trend are also reported in Fig. 2. The results in Table 1 show that in 2015 the maximum value of agricultural machinery was 34,357.09 10^3kw, while the minimum value was 13,994 10^3kw in 1989 for all crops. The descriptive statistics show us that either our selected variable is normal or not. To

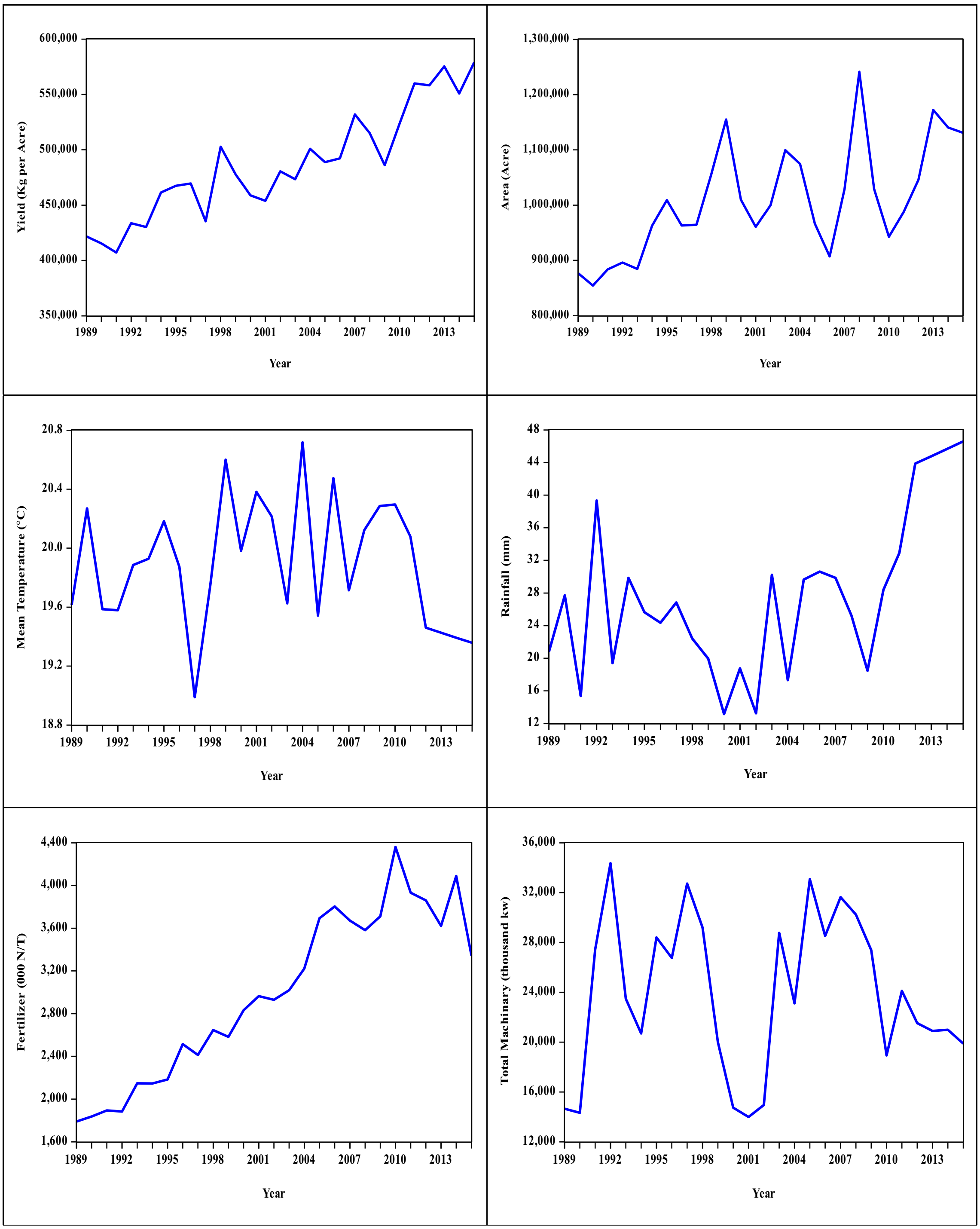


Fig. 2 Trend of the study variables in Pakistan from 1989 to 2015

check the normality of all variables, we adopt Jarque-Bera test, which shows us that the study variables are insignificant. When probability value is greater than 0.05 (*P*), this shows that the residuals are normal and when the probability value is less than 0.05, then we called that residuals are not normal (significant).

Unit root test results

First of all, we need to find out the stationarity properties of all variables which we are using in this research work. For this purpose, we used the unit root tests to evaluate the stationarity of the data. If our data is not stationary, then our results will be meaningless and spurious. To avoid spurious regression, we first check the unit root tests. We run the augmented Dickey and Fuller (ADF) test that was pioneered by Dickey and Fuller (1979) and Phillips-Perron (PP) unit root tests (Phillips and Perron 1988). The result of ADF for sugarcane crop shows us that the variables Ln*Y*, Ln*A*, Ln*T*, and Ln*F* were all stationary in their level and first difference form respectively, while the finding from PP indicates that the variables Ln*A* and Ln*F* were both not stationary in level form but become stationary at their first differences at the 1% level of significance. Variable Ln*R* was not stationary in their level form, but become stationary at their first difference form in ADF, while in PP, it was stationary in both level form and at first difference at 1% level of significance. The last variable Ln*M* was not stationary at level form and becomes stationary at first difference in ADF test while PP test also shows that it is not stationary in level form but becomes stationary at first difference at 1% level of significance. The unit root test result for sugarcane crop is shown in Table 3.

Lag order selection criteria

In order to determine the optimal number of lags for the model, we run unrestricted vector autoregression (VAR) lag selection criteria. It is important to find out that how many lags to be used in our model. Table 4 formulates so many lag selection criteria for the model but most commonly use criteria such as Akaike Information Criterion (AIC) (Akaike 1974) and Schwarz Information Criterion (SIC) (Schwarz 1978). The Akaike Information Criterion reveals that lag 2 is the best chosen lag value for sugarcane crop in our model. Previous studies (Ali et al. 2019a, b; Ali et al. 2020; Ben Jebli and Ben Youssef 2017; Farhani and Ozturk 2015; Khim and Liew 2004; Naseem et al. 2020; Rauf et al. 2018; Xu and Lin 2017) used the AIC criteria to detect the number of lag length in the ADF test.

ARDL bound test for results

Before running the ARDL model, first of all we should find out the co-integration between our study variables. If the co-integration exists, then we can test long-run and short-run relationships among the studied variables. Table 5 shows the ARDL bound test for co-integration. The computed results for sugarcane crop indicate that the *F*-statistics calculated value is 3.231899, which is in between the lower bound and the upper bound value at 5% significance level, so it is best to employ the ARDL model in such a case or situation. Therefore, the null hypothesis of no co-integration was rejected. The ARDL model results indicated that there is existence of long-run relationship between the variables when the sugarcane crop yield per unit area is used as the dependent variable (Table 6).

Long-run estimates analysis

From the estimation of ARDL bound testing results which shows that there is existence of co-integration among the studied variables, we can estimate the long-run and short-run relationship between sugarcane crop yield per unit area and the climate change factors and technical progress. The results of the long-run coefficient are presented in Table 7, which shows that area, rainfall, and fertilizer use are positive and statistically significant. It means that 1% increase in area, rainfall, and fertilizer use will lead to a 0.29%, 0.14%, and 0.18% increase in sugarcane yield per unit area, respectively. The findings

Table 3 Unit root test results for sugarcane crop

Variables	ADF		PP	
	Level *t*-statistic	1st difference	Level *t*-statistic	1st difference
Ln*Y*	− 4.472984***	− 4.870544***	− 4.476888***	− 19.24569***
Ln*A*	− 5.311344***	− 5.418932***	− 3.136029	− 6.960250***
Ln*T*	− 4,486465***	− 8.989280***	− 4.492645***	− 14.38753***
Ln*R*	− 1.426865	− 12.11546***	− 4.065650***	− 12.11546***
Ln*F*	2.508406***	− 4.687338***	− 0.712632	− 7.666754***
Ln*M*	− 2.910804	− 5.265888***	− 2.956002	− 5.261816***

***, **, and * stand for 0.01, 0.05, and 0.10 significance levels, respectively. Source: Author's own estimation

Table 4 VAR lag order selection criteria

	Lag	LogL	LR	FPE	AIC	SIC	HQ
Sugarcane	0	135.6387	NA	1.26e−12	− 10.37110	− 10.07857	− 10.28996
	1	212.4570	110.6183*	5.28e−14	− 13.63656	− 11.58885*	− 13.06861
	2	256.0661	41.86474	5.15e−14*	− 14.24529*	− 10.44240	− 13.19053*

Source: Author's formation

LR sequential modified LR test statistic (each test at 5% level), *FPE* final prediction error, *AIC* Akaike information criterion, *SIC* Schwarz information criterion, *HQ* Hannan-Quinn information criterion

*Lag order selected by the criterion

also estimate that mean temperature is positive but not statistically significant. Furthermore, the agricultural machinery coefficient is negative and significant in nature which means that 1% increase in machinery use will lead to a 0.04% decrease in the sugarcane yield per unit area. Air temperature is directly related to solar radiation and also influences the growth and development of sugarcane because of its effect on chemical reaction speeds and internal transport processes (Cardozo et al. 2014). Optimal air temperature (28–30 °C) is one of the most important factors for maximizing sugarcane production (Carr and Knox 2011). Reductions in sugarcane biomass accumulation due to lower air temperatures during autumn-winter are well documented (Donaldson et al. 2008; Singels et al. 2005). This process is an important part of crop ripening, because at low temperatures, higher amount of sucrose is stored in stems due to reductions in the demand related to vegetative growth (Nilceu Piffer Cardozo and Sentelhas 2013). Studies revealed that crop yields have been affected by the variability of temperature, rainfall, and the interaction between them, and climate change impacts will be different across locations, types of crop, scenarios, and farmer adaptation (Attavanich and McCarl 2013; Cammarano et al. 2019; David et al. 2011; Raymundo et al. 2018; Zhao et al. 2017).

Short-run estimates analysis

Based on the ARDL bounds test approach, the empirical findings indicate that there is a short-run relationship among the variables. For sugarcane crop, the coefficient of cultivation area and rainfall are both positive and statistically significance at 1% level. This implies that in the short run, cultivation area and rainfall will play a vital role in increasing the sugarcane yield in Pakistan. The results estimate that 1% increase in the sugarcane cultivation area and rainfall leads to an increase in the sugarcane yield per unit area by 0.501% and 0.125% respectively (Table 8). In short-run estimates, the mean temperature has positive and non-significant impact on the sugarcane yield. The results also estimate that the coefficient of machinery use is negative and statistically not significant which means that a 1% increase in machinery use will lead to a 0.06% decrease the sugarcane yield per unit area.

The short-run findings can also demonstrate that there is error correction term (ECT) which shows the co-integration relationship among the variables. The coefficient of ECT(−1) is negative and statistically significant at 1% level, which indicates that approximately 1.68% disequilibria from the previous year's shock converge to the long-run equilibrium in current year.

ARDL diagnostic tests analysis

After the confirmation of the co-integration relationship for different variables, the cumulative sum (CUSUM) and cumulative sum of square of the recursive residuals (CUSUMsq) were implemented to run the ARDL model in a befitting manner. As suggested by Brown et al. (1975), the CUSUM and CUSUMsq tests were employed based on the recursive regression residuals. This test shows that if the statistics line fell inside the critical bounds at 5% level of significance, it would recommend that the calculated results of the coefficient of the ARDL model were stable. Figure 3 shows that the sugarcane crop statistics lie within the 5% critical lines, so it means that

Table 5 ARDL bound test for co-integration

Model	*F*-statistics	Critical value	Lower bound value	Upper bound value	Conclusion
ARDL (1, 0, 1, 1, 1, 0) *k*(5)	3.231866	10%	2.26	3.35	Co-integration
		5%	2.62	3.79	
		2.5%	2.96	4.18	
		1%	3.41	4.68	

Source: Author's formation

Table 6 Breakpoint unit root test

Variable	At level			At 1st difference		
	Break date	*T*-statistics	Probability	Break date	*T*-statistics	Probability
Ln*Y*	2000	− 5.826901	< 0.01	2011	− 7.503844	< 0.01
Ln*A*	2004	− 6.560491	< 0.01	2012	− 7.185907	< 0.01
Ln*T*	2011	− 6.334617	< 0.01	1993	− 8.964557	< 0.01
Ln*R*	1998	− 6.239820	< 0.01	2009	− 12.99189	< 0.01
Ln*F*	2012	− 4.402773	0.1662	1993	− 6.769418	< 0.01
Ln*M*	2005	− 4.880807	0.0471	2003	− 6.246303	< 0.01

the model coefficients are stable and we can run the ARDL model without any doubt. A number of researchers have also conducted CUSUM and CUSUMsq tests for checking the stability of the model (Afzal et al. 2010; Ali et al. 2020; Ali et al. 2019a, b, c; Huang et al. 2011; Lee et al. 2003; Ploberger and Kramer 1992; Rehman et al. 2019; Seker et al. 2015; Westerlund 2005; Xiao and Phillips 2002). We also run some other diagnostics tests for the goodness of ARDL model using in this study, which concludes positive results for the selected variables. These diagnostics tests consist of serial correlation LM test, Heteroskedasticity test and Normality test which are displayed in Table 9 and Fig. 4. The stability vector autoregression (VAR) test is proposed by Pesaran and Pesaran (1997), who demonstrated the inverse root of AR polynomial estimation. The results from the model (Fig. 5) exhibits that all the red triangular shape structures are within the blue circle, which indicates that our model is well designed for this study.

Pairwise Granger causality test

This study also employed a pairwise Granger causality test (Granger and Jji 1988) to determine the robustness of the model. The pairwise Granger causality test is displayed in Table 10, which exaggerates the directional linkages among the study variables at a time. The outcomes of the Granger causality test affirm that there is unidirectional causality between Ln*F* and Ln*Y*. The results show that there is a bidirectional causality between Ln*A* to Ln*Y*, Ln*F* to Ln*A*, and Ln*R* to Ln*T* respectively (Table 10).

Impulse response function and variance decomposition analysis

Finally, the study employed impulse response analysis between Ln*Y*, Ln*A*, Ln*T*, Ln*R*, Ln*F*, and Ln*M* to describe random innovations among them. As the pairwise Granger causality test does not indicate any random response, so in this case, we have to run the impulse response analysis. Figure 6 displays that the response of sugarcane crop yield (Ln*Y*) to area (Ln*A*) and temperature (Ln*T*) is insignificant within 10-period horizons, while the response of sugarcane crop yield (Ln*Y*) to rainfall (Ln*R*) and fertilizer use (Ln*F*) is significant within 10-period horizons respectively. On the other hand, the initial response of sugarcane crop yield (Ln*Y*) to machinery use (Ln*M*) is insignificant in the beginning. A one standard deviation shock to machinery use (Ln*M*) causes sugarcane crop yield (Ln*Y*) to exhibit an up-and-down motion within a 10-period horizon. Figure 7 illustrates the response of area (Ln*A*), temperature (Ln*T*), rainfall (Ln*R*), fertilizer use

Table 7 Results of long-run coefficients from ARDL (1, 0, 1, 1, 1, 0) model

	Variable	Coefficient	Std. Error	*t*-statistic	Prob.
Sugarcane	Ln*A*	0.297920***	0.049697	5.994756	0.0000
	Ln*T*	0.608166	0.368304	1.651263	0.1182
	Ln*R*	0.140154***	0.020563	6.815862	0.0000
	Ln*F*	0.189472***	0.020447	9.266643	0.0000
	Ln*M*	− 0.040187***	0.013573	− 2.960770	0.0092
	C	5.592449***	1.427762	3.916935	0.0012

***, **, and * stand for 0.01, 0.05, and 0.10 significance levels, respectively. Source: Author's formation

Table 8 Results of short-run coefficients from ARDL (1, 0, 1, 1, 1, 0) model

	Variable	Coefficient	Std. error	*t*-statistic	Prob.
Sugarcane	*D*(Ln*A*)	0.501595***	0.117934	4.253166	0.0006
	D(Ln*T*)	0.177429	0.356795	0.497287	0.6258
	D(Ln*R*)	0.125319***	0.028763	4.356919	0.0005
	D(Ln*F*)	0.176573*	0.084261	2.095557	0.0524
	D(Ln*M*)	− 0.067661**	0.025149	− 2.690412	0.0161
	ECT(−1)	− 1.683657***	0.220847	− 7.623645	0.0000

Cointeq = Ln*Y* − (0.2979*Ln*A* + 0.6082*Ln*T* + 0.1402*Ln*R* + 0.1895*Ln*F* − 0.0402*Ln*M* + 5.5924)

***, **, and * stand for 0.01, 0.05, and 0.10 significance levels, respectively. Source: Author's formation

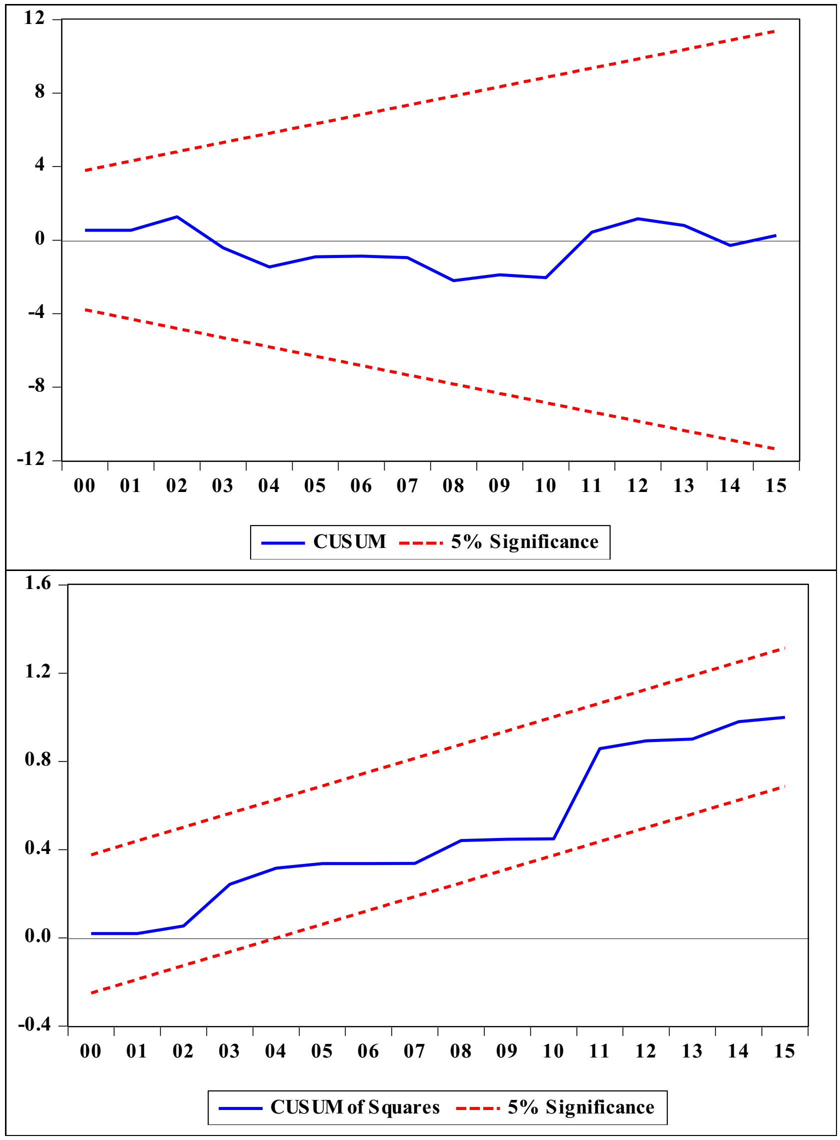


Fig. 3 Sugarcane CUSUM and CUSUM square

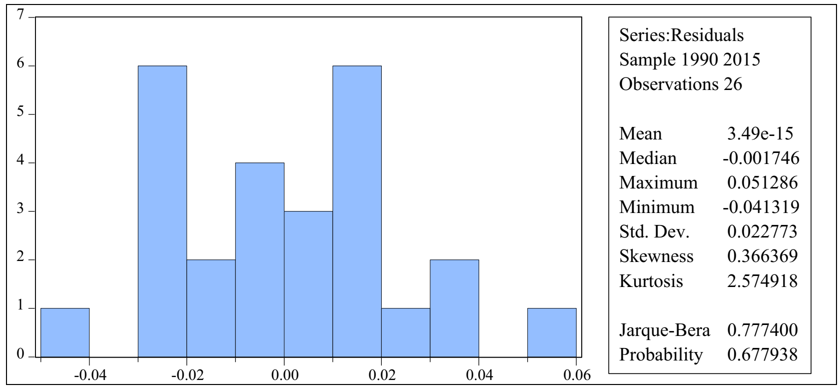
(Ln*F*), and machinery use (Ln*M*) to sugarcane crop yield (Ln*Y*).

In addition, Cholesky's technique of variance decomposition to random innovation affecting the variables in the VAR (Payne 2002) is estimated in Table 11. The outcome points out that almost 28.6% of the future fluctuations in Ln*Y* is due to shocks in the Ln*A*, 0.95% of future fluctuations in the Ln*Y* is due to shocks in Ln*T*, 0.13% of future fluctuations in the Ln*Y* is due to shocks in Ln*R*, 1.2% of future fluctuations in the Ln*Y* is due to shocks in Ln*F*, and 0.66% of future fluctuations in the Ln*Y* is due to shocks in Ln*M*, respectively. Furthermore, the table illustrated that almost 5.8% of future fluctuations in Ln*A* is due to shocks in Ln*Y*, 5.9% of future fluctuations in Ln*A* is due to shocks in Ln*T*, 0.22% of future fluctuations in Ln*A* is due to shocks in Ln*R*, 7.7% of future fluctuations in Ln*A* is due to shocks in Ln*F*, and 30.6% of future fluctuations

Table 9 Diagnostic statistics of crops

Breusch-Godfrey Serial Correlation LM test	
F-statistic	0.119511
Obs*R-squared	0.436447
Prob. F(2,14)	0.8882
Prob. Chi-square(2)	0.8039
Heteroskedasticity Test: Breusch-Pagan-Godfrey	
F-statistic	0.563098
Obs*R-squared	6.254305
Scaled explained SS	1.865092
Prob. F(9,16)	0.8076
Prob. Chi-square(9)	0.7142
Prob. Chi-square(9)	0.9934

Fig. 4 Normality test for sugarcane crop



in LnA is due to shocks in LnM. It is further evident from the data that almost 23.4% of future fluctuations in LnT is due to shocks in LnY, 0.23% of future fluctuations in LnT is due to shocks in LnA, 0.19% of future fluctuations in LnT is due to shocks in LnR, 5.5% of future fluctuations in LnT is due to shocks in LnF, and 0.64% of future fluctuations in LnT is due to shocks in LnM. Moreover, the table also displays that almost 3.1% of future fluctuations in LnR is due to shocks in LnY, 43.2% of future fluctuations in LnR is due to shocks in LnA, 30.2% of future fluctuations in LnR is due to shocks in LnT, 3.5% of future fluctuations in LnR is due to shocks in LnF, and 2.03% of future fluctuations in LnR is due to shocks in LnM. The outcome points out that almost 5.9% of the future fluctuations in LnF is due to shocks in the LnY, 4.2% of future fluctuations in the LnF is due to shocks in LnA, 8.5% of future fluctuations in the LnF is due to shocks in LnT, 1.8% of future fluctuations in the LnF is due to shocks in LnR, and 14.9% of future fluctuations in the LnF is due to shocks in LnM, respectively. Finally, the evidence from Table 10 shows that almost 38.8% of the future fluctuations in LnM is due to shocks in the LnY, 8.7% of future fluctuations in the LnM is due to shocks in LnA, 16.9% of future fluctuations in the LnM is due to shocks in LnT, 0.1% of future fluctuations in the LnM is due to shocks

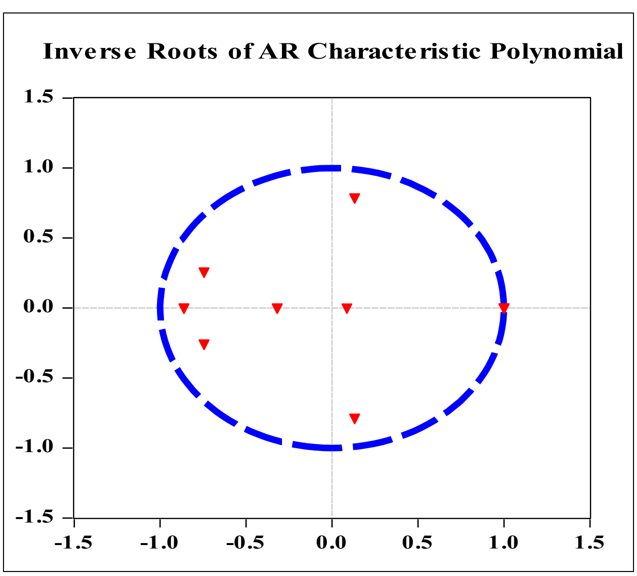


Fig. 5 Checking the stability of vector autoregression (VAR)

Table 10 Pairwise Granger causality test

Null hypothesis:	Observation	F-statistic	Prob.
LnA does not Granger Cause LnY	25	3.05235	0.0697
LnY does not Granger Cause LnA		5.81545	0.0102
LnT does not Granger Cause LnY	25	0.51960	0.6026
LnY does not Granger Cause LnT		0.31871	0.7307
LnR does not Granger Cause LnY	25	0.35812	0.7034
LnY does not Granger Cause LnR		0.96670	0.3974
LnF does not Granger Cause LnY	25	3.08324	0.0681
LnY does not Granger Cause LnF		0.45404	0.6414
LnM does not Granger Cause LnY	25	0.19258	0.8263
LnY does not Granger Cause LnM		1.13451	0.3414
LnT does not Granger Cause LnA	25	0.91603	0.4162
LnA does not Granger Cause LnT		0.26124	0.7727
LnR does not Granger Cause LnA	25	1.11934	0.3461
LnA does not Granger Cause LnR		1.52644	0.2416
LnF does not Granger Cause LnA	25	5.43446	0.0130
LnA does not Granger Cause LnF		5.69962	0.0110
LnM does not Granger Cause LnA	25	0.27085	0.7655
LnA does not Granger Cause LnM		2.06558	0.1529
LnR does not Granger Cause LnT	25	3.87107	0.0379
LnT does not Granger Cause LnR		4.49741	0.0244
LnF does not Granger Cause LnT	25	0.19761	0.8223
LnT does not Granger Cause LnF		0.83833	0.4471
LnM does not Granger Cause LnT	25	0.47148	0.6308
LnT does not Granger Cause LnM		0.41811	0.6639
LnF does not Granger Cause LnR	25	1.45610	0.2568
LnR does not Granger Cause LnF		1.28244	0.2992
LNFF does not Granger Cause LnR	25	1.27413	0.3014
LnR does not Granger Cause LNFF		0.35164	0.7078
LnM does not Granger Cause LnF	25	0.61012	0.5531
LnF does not Granger Cause LnM		0.20261	0.8183

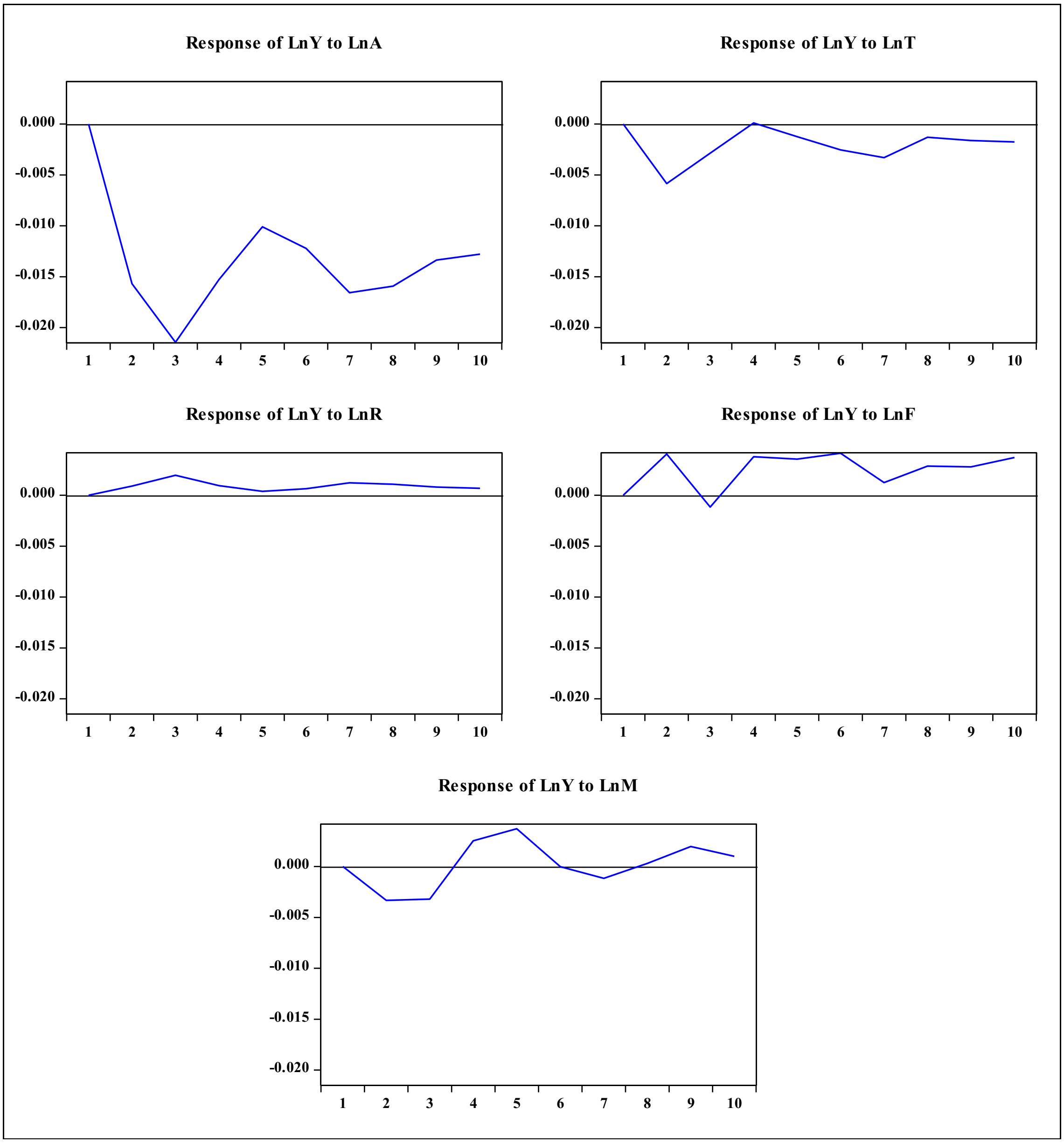


Fig. 6 Impulse response of LnY to Cholesky one S.D. Innovation

in LnR, and 13.4% of future fluctuations in the LnM is due to shocks in LnF, respectively.

Conclusion and policy implications

In this study, we analyze the relationships among the sugarcane crop yield (Y), the area of selected crop cultivation (A), mean temperature (T), the total quantity of fertilizer use (F), rainfall (R), and machinery use (M) in Pakistan over the period between 1989 and 2015. The aim of this study is to find out the impact of climate change on the sugarcane crop yield and the technical advancement effect, i.e., aggregate quantity of fertilizer used and total agricultural machinery used, on selected crop unit area. The ARDL model was employed to achieve the influence of climate change and technical factors on the yield per unit area of sugarcane crop. There is co-integration exist among the variables by employing the ARDL bound test for co-integration.

The finding of our study shows that some climatic variables have significantly negative effect on the sugarcane crop yield, while the remaining variables are positively significant. The results of both ADF and PP tests for sugarcane crop revealed that the variable yield, mean temperature, and fertilizer use were stationary at both level and first difference form. The outcomes also show that variable machinery use was not stationary at level forms while it became stationary at first difference form. The results of the ARDL bounds testing approach

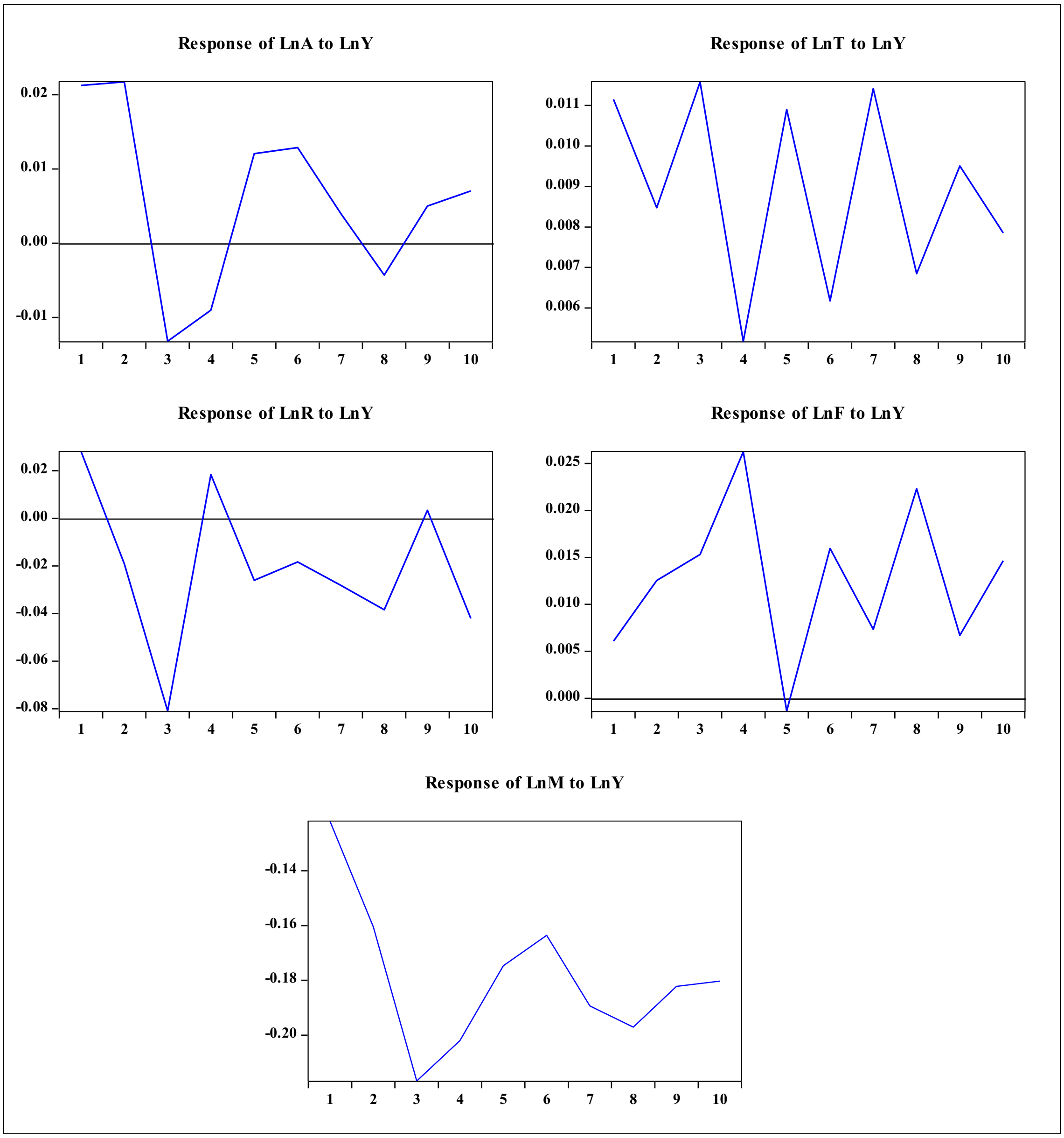


Fig. 7 Impulse response of other study variables to Cholesky one S.D. Innovation in LnY

to co-integration revealed that there is a long-run and short-run relationship among the variables. The F-statistics value of sugarcane was 3.231866, which is in between the lower bound value and upper bound value at 5% significant level. The results of the long-run relationship showed that the coefficient of area, rainfall, and fertilizer use were positive and significant, mean temperature was positive and not significant, while machinery use was of negatively significant relationship with sugarcane crop yield, respectively. The results of short-run relationship estimated that the value of error correction term (ECT) was −1.683 and significant at 1% level for sugarcane crop. The outcomes of the pairwise Granger causality test indicated that there exist both unidirectional and bidirectional causalities between the study variables. The paper aimed to employ variance decomposition and Cholesky ordering to find out the future effect of selected variables on sugarcane crop yield in the VAR model.

This research recommends that Pakistan needs to solve main challenges of its agricultural sector, particularly in the production of sugarcane. The results of this research work have a variety of policy implications that could ensure persistent improvements in the sugarcane yield per unit area and food protection under climate change in Pakistan. Large-scale mechanical activities and rapid growing may be useful initiatives for raising the yield of sugarcane. Therefore, mechanical activities to agriculture could be supported by central and local governments. There is a need to increase agricultural output by productive farming processing techniques.

Table 11 Variance decomposition using Cholesky factors (ordering: Ln*Y*, Ln*A*, Ln*T*, Ln*R*, Ln*F*, and Ln*M*)

Period	S.E.	Ln*Y*	Ln*A*	Ln*T*	Ln*R*	Ln*F*	Ln*M*
Variance decomposition of Ln*Y*							
1	0.045107	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.049609	87.46000	9.999213	1.394933	0.033070	0.663593	0.449191
3	0.056055	74.78318	22.47209	1.354064	0.147730	0.562255	0.680679
4	0.060940	71.79415	25.30162	1.145943	0.148657	0.863041	0.746584
5	0.066202	73.13177	23.76793	1.006195	0.129182	1.019725	0.945192
6	0.070175	72.56252	24.19037	1.026993	0.123583	1.255328	0.841200
7	0.074097	70.11168	26.69698	1.119233	0.138451	1.154273	0.779380
8	0.077741	68.46723	28.44868	1.044496	0.145323	1.184664	0.709605
9	0.081468	68.37362	28.59367	0.991219	0.141916	1.195586	0.703988
10	0.084841	68.31232	28.63664	0.957366	0.137428	1.293267	0.662984
Variance decomposition of Ln*A*							
1	0.060623	12.27840	87.72160	0.000000	0.000000	0.000000	0.000000
2	0.091313	11.07406	73.99592	4.398740	0.063556	0.426911	10.04082
3	0.107791	9.450815	55.17531	6.258009	0.262679	5.190635	23.66255
4	0.116201	8.733673	49.47175	6.296117	0.303695	6.409185	28.78558
5	0.124692	8.521272	50.91425	5.747823	0.279642	7.196828	27.34019
6	0.135746	8.090024	53.63236	5.426145	0.236050	6.294979	26.32045
7	0.145153	7.151384	51.48111	6.070268	0.226575	7.144847	27.92582
8	0.152243	6.580478	49.42362	6.102690	0.239128	7.330223	30.32386
9	0.158770	6.149999	48.81114	6.156092	0.238666	7.990314	30.65379
10	0.165649	5.830169	49.61776	5.954340	0.224585	7.730493	30.64265
Variance decomposition of Ln*T*							
1	0.026060	18.30573	0.402615	81.29165	0.000000	0.000000	0.000000
2	0.030915	20.52371	0.639758	72.65042	0.135576	5.700682	0.349846
3	0.036259	25.12237	0.482065	69.28125	0.197843	4.211569	0.704900
4	0.040813	21.43750	0.406635	70.61221	0.308135	6.628713	0.606805
5	0.043962	24.62294	0.398020	68.13036	0.288362	5.788698	0.771625
6	0.048488	21.86323	0.329128	70.25146	0.280331	6.631978	0.643876
7	0.051254	24.52902	0.306629	68.17972	0.254115	5.960439	0.770072
8	0.054707	23.09674	0.272654	69.67583	0.231701	6.041206	0.681873
9	0.057035	24.02761	0.256115	69.14845	0.215274	5.674566	0.677980
10	0.059921	23.48781	0.236541	69.91191	0.196217	5.521952	0.645575
Variance decomposition of Ln*R*							
1	0.215816	1.680204	28.91200	28.29292	41.11487	0.000000	0.000000
2	0.294392	1.323105	32.13056	43.24983	22.66928	0.026635	0.600592
3	0.382919	5.254469	43.64752	27.09283	23.59889	0.016337	0.389960
4	0.429074	4.368644	39.76621	33.81236	19.79772	0.615142	1.639925
5	0.466567	4.006374	42.42946	30.21172	20.79414	0.562500	1.995818
6	0.505670	3.541548	40.74742	33.05160	19.23794	1.591867	1.829618
7	0.548318	3.276376	43.19889	31.13103	18.68593	1.853014	1.854756
8	0.580020	3.367045	43.00684	30.71593	18.27971	2.849578	1.780901
9	0.613945	3.008182	43.24209	30.93383	17.81603	2.863047	2.136823
10	0.640377	3.196663	43.22706	30.22282	17.74869	3.566084	2.038685
Variance decomposition of Ln*F*							
1	0.065171	0.870180	5.013710	8.695472	2.574040	82.84660	0.000000
2	0.080402	3.007466	12.09546	8.118870	1.833134	59.56834	15.37673
3	0.116971	3.135731	6.105339	9.462147	1.924745	67.10986	12.26218
4	0.126225	7.018250	5.498893	8.308538	1.916461	61.72083	15.53703
5	0.143885	5.410070	4.645726	8.671386	1.857778	66.58796	12.82708
6	0.150563	6.064200	5.660474	8.164113	1.833908	63.79147	14.48583
7	0.166440	5.157529	4.713706	9.057837	1.813763	65.56469	13.69248
8	0.174045	6.361334	4.475960	8.544238	1.824247	63.75602	15.03820
9	0.185425	5.734902	4.069787	8.790665	1.840101	65.23463	14.32992
10	0.191562	5.957557	4.275879	8.508277	1.834288	64.51028	14.91372
Variance decomposition of Ln*M*							
1	0.275481	19.61040	1.344208	26.20775	0.082927	11.96005	40.79466
2	0.384587	27.46534	2.052637	21.10286	0.209910	17.27171	31.89754
3	0.496865	35.47442	7.307628	20.23273	0.258861	13.22756	23.49880
4	0.582880	37.78668	8.792859	18.65082	0.195661	12.73353	21.84045
5	0.648140	37.82393	8.813613	17.48492	0.176142	12.81642	22.88498
6	0.707052	37.13246	8.134613	17.67836	0.157572	13.69249	23.20450
7	0.763556	37.98867	8.482423	17.53779	0.142037	13.25907	22.59001
8	0.820658	38.65408	8.724053	17.35928	0.123073	13.31722	21.82229
9	0.869492	38.82555	8.946284	17.15183	0.111587	13.00705	21.95770
10	0.916412	38.82024	8.754676	16.94102	0.100454	13.42166	21.96195

Furthermore, agro-technicians could be structured to instruct farmers on the appropriate use of fertilizers, depending on the characteristics of climate, the soil, variety of sugarcane, and growth period features.

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Data availability All relevant data are within the paper.

Declarations

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