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R&D Innovation Adoption, Climatic Sensitivity, and Absorptive Ability Contribution for Agriculture TFP Growth in Pakistan

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Abstract: Innovation adoptions in agriculture sustain high total factor productivity (TFP) growth and overcome a potential production gap, which is beneficial for food security. Research and development (R&D) innovation adoption in agriculture sector is dependent on producers' willingness to adopt, knowledge capital spillovers, and financial capacity. This research aims to investigate the impact of R&D innovation adoption and climate factors on agriculture TFP growth in Pakistan. The annual time series data were collected from different sources for the period of 1972–2020. For measuring the agriculture TFP, this study adopted the Cobb Douglas and Translog production functions. To analyze the impact of R&D innovation adoption and climate change on agricultural productivity, the dynamic autoregressive distributive lag (ARDL) and two-stage least square (TSLS) approaches were applied for regression analysis. The study outcomes highlight that the agricultural innovation adoption has a significantly positive impact on agriculture TFP growth in Pakistan with weak farmers' absorptive ability. According to the results, agriculture tractors, innovative seed distribution, and fertilizer consumptions make a significantly positive contribution to agriculture TFP growth. Further, rainfall shows a positive and significant impact on agricultural productivity, where a moderate climate is beneficial for agricultural productivity. The estimation results contain policy suggestions for sustainable R&D adoption and agrarians' absorptive ability. Based on the obtained results, it has been suggested that producers should focus on R&D innovation adoption to attain higher productivity. The government needs to emphasize innovative technology adoption, specifically to implement the extension services to increase farmers' education, skills based training, and networking among the farmers to enhance their knowledge capital and absorptive ability. The farmers should also focus on the adoption of climate smart agriculture that can be achieved through the proper utilization of rainwater. For this purpose, the government needs to develop small community dams and large-scale dams for better use of rainwater harvesting.

Keywords: technology adoption; climatic variation; absorptive ability; agriculture TFP growth; TSLS; Pakistan

1. Introduction

The Global Agriculture and Productivity (GAP) report of 2020 shows that an additional 71–100 million people fell into extreme poverty due to the COVID-19 shutdown, and 235 million people are at high risk of acute hunger [1]. Globally, 20–40% of crop yield is lost each year due to pest attacks, while around 81 million people's food can be consumed by large swarms annually [1]. Agriculture innovation and its adoption is an essential element to overcome the global food security and poverty challenges. Climatic vulnerability harms the agriculture output and creates food insecurity problems, especially in developing countries [2]. These food insecurity challenges may even lead to a negative impact on a global scale. Sustainable agriculture research and development (R&D) and its spillover shocks, climatic protection strategies, water management policies, and technology adoption in the agriculture sector have significant potential to save the world from a harmful climate and upcoming food security challenges. The adoption of innovative technology in the agriculture sector provides mechanization and permits adaptation of the optimum level of input. Utilizing optimal agriculture inputs reduces the labor demand, monitoring cost, water scarcity challenges, and soil erosion. Further, an optimal input provides digital logistics and trustworthy consumers to the farmers, through which agrarians can maintain high yield and profitability. The combined collaborative efforts between government and private partners can enhance innovative adoptions in agriculture [3]. A country's efforts toward agriculture innovation and adoption perform an essential role in farm and off-farm agriculture growth [4]. Agriculture innovations consolidate the higher level of output and sustain food availability in both developed and developing countries, which is also helpful in food accessibility through international agriculture trade.

The agriculture total factor productivity (TFP) increases when agrarians adopt and efficiently utilize innovative technology to attain a higher yield with fewer input resources. Additionally, technology adoption in the cropping sector (e.g., innovative and hybrid seeds, fertilizers, agri-technology, water efficiency, water management technology, hydroponic technology, etc.) intensifies the output, product efficiency, and profitability. Similarly, through the usage of animal genetics, breed varieties, and veterinary medicines, farmers can get more milk, meat, and eggs with fewer inputs [1,5–7]. Fundamental ways to mitigate agriculture risks are R&D, innovation adoption, and enhanced agronomic expertise. The farmer's expertise improves through their access to education, extension services, training, skill-based workshops, community-led solutions, and networking with research institutions [8,9]. To enhance agricultural productivity and agrarians' expertise, Steensland [1] highlights the policy priorities to adopt at a country level, which include R&D funding, extension services, agrarians' training, accelerating innovation adoption, networking policies, and financial management.

To feed the 10 billion projected global population in 2050, global agriculture requires a higher annual TFP growth of 1.73% as compared to current TFP growth, which is at 1.63% [1]. In order to sustain the global food requirement, the government R&D spending in agricultural innovation is essential for agriculture productivity, food security, and environmental sustainability [9]. The government should provide agricultural innovation, such as rival goods, especially innovative seed varieties and other essential agriculture technologies. Further, the negligence of government towards agriculture R&D puts future agri-TFP growth at high risk [10]. Globally, the private sector accounted 52.5% of domestic agriculture R&D spending in 2011 as compared to 42% in 1980 [9]. A paradigm shift happened in agriculture R&D spending from public to private, and worldwide from higher income countries to middle-income countries (like USA to Brazil, China, and India) [9,11]. Further, Chai et al. [12] point out that the Chinese government spent the two-thirds of R&D funding on agriculture from their total, outspending the USA in both public and private sector agriculture expenditures.

Innovation adoption in agriculture is an essential element to increase farm level productivity, farmers' welfare, and to ensure the food security. However, the technological spillovers and adoption are heterogeneous across the farms, regions, and countries, creating heterogeneity in farmers' welfare, income equality, and poverty [13–15]. Similarly, Hurley et al. [16] argued that agriculture R&D spending has a high rate of return and provides 2.5–5% productivity over the non-R&D spenders. In addition, Diederen et al. [17] concluded that the farmers who adopt innovation early gain higher profitability over later adopters, so the period of innovation adoption is as important as innovation itself. Maffioli et al. [18] found the positive effect of technology adoption on agriculture output, whereas the improved adoption rate of seed varieties is certainly weak. Similarly, Gallardo & Sauer [19] investigated the role of laborsaving and technological adoption in agriculture output and found that innovative adoption performs a successive role in agriculture productivity. Bucci et al. [20] worked on precision agriculture technology (PAT) adoption in Italy and concluded that the chosen PAT farmers face various obstacles like geographical area, cultural barrier, limited information about benefits, small farm size, and low appreciating benefits over the cost of PAT chosen. Additionally, ref. [1,21] reviewed the existing literature and found that weak extension services are major hurdles in agriculture technology diffusion and earlier adoption.

Investment in agriculture innovation performs an influential role in agriculture growth. Evidence shows that agriculture investment has a high rate of return, and investment in tractor and tube-well has a significant impact on agriculture production in Punjab, Pakistan [22]. Chandio et al. [23] revealed that farmers' financial access and technology adoption improved cereal production, whereas carbon emission and harmful climate negatively affected cereal output. Shabbir & Yaqoob [24] argued that agriculture innovative inputs have stabilized the cotton production in Pakistan and that hybrid seed, mechanization, and cotton yield area are important reasons for the growing output. Abdullah & Samah [25] studied the appreciative measures of agriculture technology and concluded that the farmers' education, willingness to learn about advanced technology, updated knowledge of extension workers, extension services, and the area's physical condition all perform an essential role in technology transformation and agriculture output. The updated knowledge of extension workers can help in training and educating the farmers to prepare for agriculture innovation adoption. In a similar line, Sjakir et al. [26] found that agri-field schools modernized agrarian expertise and extension services, playing an effective role in technology expansion. This revealed that the farmers who attended such field schools have improved knowledge and productivity.

In Pakistan, the agriculture share of GDP is decreased because of the lacking government consideration, poor agriculture development expenditure, weak extension services, technological availability, low agriculture financial services, farmers' education, and lack of agrarians' management skills [27,28]. The agriculture innovation adoption (like innovative seeds, new production process, water management strategies, fertilizers, pesticides, and advance agri-technology) and favored production environment have a noteworthy impact on the agriculture production of Pakistan. The innovation in agriculture technology has the potential to increase the output that leads to an increase in farmers' income, consumption, standard of living, and poverty alleviation in rural areas [28–31]. Additionally, Ali & Behera [27] found that the wealthier and educated young farmers are more willing to adopt alternative irrigation technology, but the frequent energy shortage and lack of financial credit facilities creates hurdles in irrigation technology adoption. Similarly, Chandio et al. [32] argued that farm size, labor, credit, and fertilizer usage perform a positive role in rice productivity, while technical efficiency indicates that rice farmers are highly efficient with rice production technology.

This paper contributes to the literature in following ways. First, the perpetual inventory methodology (PIM) was used to calculate the net capital stock of the agriculture sector of Pakistan [33]. For necessary conditions, the initial capital stock is calculated from the gross capital investment of the agriculture in Pakistan. Second, the TFP is calculated by adopting the Cobb Douglas production function in the form of Translog function. Thirdly, the existing literature regarding agriculture innovation adoption focused on a cross-section framework, either cross-country or across the regions, while this study adopts the time series empirics for country-specific analysis. This research not only focused on technology adaption measures, but also incorporated the laborer absorptive capacity in the agriculture sector. Fourth, the literature review regarding technology adoption in the agriculture sector of Pakistan [13,34–37] is not readily available and most studies focused on analyzing the impact of agriculture inputs on value addition. This unique study comprehensively measured agriculture TFP growth and investigates the dependency relationship between technology adoption and absorptive ability factors on TFP growth. Fifth, simultaneously, numerous diagnostic tests were applied for quantitative results, and the problem of endogeneity was detected through a different sort of analysis. To avoid the endogeneity problem, two stage least square (TSLS) regression analysis was adopted to provide an instrumental specification to resolve the endogeneity problem.

At the beginning of the twenty-first century, R&D innovation revolutionized the agriculture production process and social well-being of the farmers. Globally, the increasing role of R&D in economic performance of agriculture sector is a key motivation of this research. R&D contributes through potential and intensive utilization of resources, increasing efficiency of human resources, availability, and adoptability of internal and external innovation. Agriculture R&D spending has a negligent share in the GDP of Pakistan, which is creating the potentiation gap in agriculture TFP growth. Existing literature suggested that agriculture performance of developed and developing countries is dependent on R&D spillovers, knowledge shocks, adoption of innovation, and farmers absorptive ability [38–40]. However, current studies have presented an overview of R&D spillover, but empirical studies are very rare in the case of Pakistan and not focused on farmers absorptive ability. The role of R&D spillovers in agriculture productivity growth in the context of empirical manners is missing in case of Pakistan. At present, the existing literature is unable to answer the following questions: Does technological adoption perform a productive role in agriculture output in Pakistan? Does the agriculture investment affect the volatility of TFP growth? Does the R&D innovation adoption perform a significant role in the agriculture TFP of Pakistan? Does the climatic variation affect the agriculture TFP growth in Pakistan? Does the human capital perform a fruitful role in agriculture TFP? Do the farmers have the absorptive capacity to adopt the agriculture innovation for higher output? By keeping in mind such research questions and gaps in the existing literature, this research comprises the following objectives: calculating the TFP growth in Pakistan and investigating the impact of technological adoption on agricultural TFP. The purpose of this research is to explore the role of R&D adoption in agriculture TFP growth in Pakistan. This study investigates the farmers absorptive ability regarding R&D innovation in the agriculture sector. This research also examines the effects of climatic variation in agriculture TFP.

2. Materials & Methods

The agriculture R&D investment and innovation adoption performs a productive role in agriculture output. Agriculture R&D brings innovative seed varieties, new sowing and harvesting techniques and technologies, and product efficiency to boost the agriculture output. R&D innovation enhances the irrigated water efficiency and protects the crops from climatic vulnerability. In this adoption, farmers' education, management skill, ground-level experience, willingness, and financial capacity to opt for the innovation and absorptive ability are crucial factors. The evidence shows that agriculture R&D has a higher rate of return and the adoption of agriculture technology, fertilizers, and innovative seeds has a significant impact on agriculture TFP growth [22,23]. Numerous approaches are available to compute the TFP growth, such as index numbers, stochastic frontiers, ordinary least square, etc. However, such approaches are not applicable in this circumstance and considering the availability of data [41]. The agriculture TFP growth is measured through the Cobb Douglas and translog production functions due to data constraints. In addition, the Cobb Douglas-based production function measures the TFP at the aggregate level, which is appropriate to compute the TFP growth from conventional time-series data for labor and capital inputs, in addition to climatic variations. The essential assumption for the Cobb Douglas production function includes a constant return to scale in respective labor, capital, land, and climate factors in both production and input processes [42,43].

In this research, the Cobb Douglas production function is modified, according to the input requirements for agriculture cultivation and introduced climatic factors to quantify the agriculture TFP growth over the traditional production function. The purpose of incorporating climatic factors into agriculture production function is that the climatic factors are as important as capital, land, technology, and labor inputs, which are all essential for agriculture output. The adapted form of the agriculture production function is expressed as follows:

$$\mathrm{Y_t = A_t K_t^{\alpha} L_t^{\beta} CF_t^{\delta}} \tag{1}$$

In Equation (1), Y_t is agriculture output, K_t is net capital stock, L_t is agriculture labor, CF_t representing the climatic factors, and A_t is representing agriculture TFP (ATFP). 't' represents time period, and α, β, and δ represent the shares of net capital stock, agriculture labor, and climate factors, respectively. Through inverting Equation (1) into input-output ratio and applying the logarithm with its properties on both sides, $ATFP_t$ growth is calculated as follows.

$$\mathrm{ATFP_t} = \frac{\mathrm{Y_t}}{\mathrm{K_t^{\alpha} L_t^{\beta} CF_t^{\delta}}} \tag{2}$$

$$\mathrm{lnATFP_t = ln\ Y_t - (\alpha lnK_t + \beta lnL_t + \delta lnCF_t)} \tag{3}$$

As a result, Equation (3) demonstrates $ATFP_t$ growth, which is measured through agriculture inputs, such as capital stock, labor, and climatic factors. To measure the net capital stock K_t in agriculture, the perpetual inventory method was adopted [44,45].

2.1. Net Capital Stock

The rise in stock of capital is called gross capital formation and can be measured from total investment expenditure on agriculture within the economy. The gross capital formation is known as net investment in the agriculture sector by excluding the depreciation and inflationary effects. The net capital stock is a difference between gross capital formation and fixed capital consumption (known as depreciation rate or capital consumption). Depreciation rate refers to wear and tear expenditures from fixed capital to maintain capital stock in its initial condition.

The perpetual inventory methodology (PIM) approach based on ref. [46] is applied for calculating the net capital stock in agriculture [33]. In this approach, the approximation of initial capital stock, growth rate, and depreciation was incorporated. The agriculture GDP growth rate of the previous period is assumed as the current capital growth rate [41]. The estimated formulations are as follows:

$$\mathrm{K_{t+1} = I_t + (1 - d)K_t} \tag{4}$$

In notation (4), 't' represents the time, K_{t+1} is net capital stock in the agriculture sector, I_t is gross capital stock, and 'd' is the depreciation rate. However, the study focused on measuring the net capital stock in the agriculture sector, which requires the initial capital stock. For this purpose, the gross fixed capital formation is used to calculate the initial capital formation. The method to measure the initial capital is as follows:

$$\mathrm{I_o} = \frac{\mathrm{I_i}}{\mathrm{g_i + d}} \tag{5}$$

Here, in notation 5, I_o is the initial level gross fixed capital stock in agriculture, where g_i is average growth in capital formation. For this, the proxy of previous period agriculture GDP growth was taken [41]. The data of depreciation are collected from the Panne world table 10.1, to measure the net capital stock. Ref. [47] argued that depreciation is taken as the average life span of machinery (capital equipment) and growth of capital stock 'g' must be taken as the average growth of capital stock through the sample range.

2.2. Empirical Model

For agriculture productivity, the inclusive R&D factors, knowledge capital, labor force, and climatic condition have a fruitful effect on agriculture output and promote inclusive agriculture growth. Domestic R&D innovation is suitable because it matches with country land requirement, soil fertility, climatic conditions, water sources availability, rural culture, social and politic norms, and economic conditions. Internal R&D in agriculture has a compatibility with land requirement while internally developed innovative seeds, irrigation techniques, and agriculture equipment and machinery are more appropriate and productive than foreign imported technology [45,48]. The functional relationship of ATFP growth is determined to investigate the R&D adoption indicators, climate factors, and farmers absorptive ability as endogenous determinants of ATFP growth. Salim & Islam [43] worked on the significance of technology adoption and its role in agriculture $ATFP_t$ growth and concluded that the innovation adoption is an essential factor to increase the $ATFP_t$, which is largely influenced through climate factors and knowledge capital. The technology adoption is highly productive and beneficial to improve internal innovation and knowledge absorptive ability [44]. R&D innovation in the agriculture sector is measured through the Cobb Douglas production function in the Translog form. The agriculture output performance is dependent on ATFP, labor efficiency, net capital stock and cultivation land. The domestic innovation spillover is essential to increase the agriculture ATFP growth, which is largely influenced through technological spillovers, farmers' willingness to adopt, farmers' absorptive capacity, and climate factors. The modified form of the Cobb Douglas production function as follows:

$$Y_t = ATFP_t K_t^{\alpha} L_t^{\beta} M_t^{\gamma} CF_t^{\delta} \tag{6}$$

In Equation (6), Y_t is agriculture output performance while $ATFP_t$, L_t^{α}, K_t^{β}, M_t^{γ}, and CF_t^{δ} are ATFP, agricultural labor force, net agriculture capital stock, agriculture land, and climate factors, respectively. Here, 't' represents time and α, β, γ, and δ represent the respective weights of capital, labor, land, and climatic factor in agriculture. The $ATFP_t$ growth is dependent on R&D adoption in agriculture, climate factors, and agrarians' absorptive capacity.

$$ATFP_t = A_t RD_t AC_t CF_t \tag{7}$$

In Equation (7), the dependent variable is $ATFP_t$ growth and independent variables are (A_t, RD_t, AC_t, CF_t) technical progress, R&D adoption, absorptive capacity (AC), and climate factors (CF). Taking the natural log and adding intercept and residual terms in Equation (7), the final estimated model is provided.

$$LnATFP_t = \alpha_0 + \alpha_1 A_t + \alpha_2 RD_t + \alpha_3 AC_t + \alpha_4 CF_t + \varepsilon_t \tag{8}$$

Equation (8) is modified according to the availability of data and assumption concerns with the agriculture growth model [43]. In the estimated model, the interactive term of human capital is incorporated with R&D indicators to measure the farmers' absorptive capacity [44]. The estimated model to examine the role of R&D innovation adoption, climatic factors, and absorptive capacity on $ATFP_t$ growth is as follows:

$$lnATFP_t = a_0 + a_1 lnAI_t + a_2 lnAEMP_t + a_3 lnHC_t + a_4 lnRF_t + a_5 lnAT_t + a_6 lnFC_t + \alpha_7 lnSD_t + a_8 lnHCxRD_t + \pi_t \tag{9}$$

Equation (9) is the final estimated model to investigate the behavior of technology adoption channels, absorptive ability, and climate factor in ATFPt growth in Pakistan. Here, $ATFP_t$ is agriculture total factor productivity, which is a dependent variable, while the independent variables AI_t, $AEMP_t$, HC_t, RF_t, AT_t, FC_t, SD_t, and $HCxRD_t$ represent agriculture investment, employment, human capital, rainfall, agriculture tractor, fertilizer consumption, innovative seeds distribution, and interactive term to measure the absorptive ability. The description and measurement units of variables are given in Table 1. In Equation (9), alphas (α's) represent the equation coefficients and π represents the residual term. Initially, the $ATFP_t$ is considered as an exogenous variable and measured through the growth accounting technique. At the second stage, $ATFP_t$ is regressed on the indicators of technological adoption and climatic indicators. This research concerns the multicollinearity and endogeneity problem caused by technological adoption (input) factors in the estimation of ATFP and interactive term to capture the absorptive ability. The endogeneity can be overcome by including the interactive term and lagged instrumental variables in the estimated model [41], which cause the multicollinearity problems. In the estimated model, the interactive term of human capital with R&D incorporated in the model is used to overcome the endogeneity problems and measures the absorptive ability. For final analysis, the dynamic autoregressive distributed lag (ARDL) model and TSLS instrumental variable approach is applied.

Table 1. Variables and Description.

Abbreviation	Variables	Measurement Units
TFP_t	Total Factor Productivity	Measured through Cobb Douglas and Translog Production Function
AI_t	Agriculture Investment	Million Rupees
AL	Agriculture Land	Percentage share in total Land
AT_t	Agriculture Tractor	Total in numbers
$AEMP_t$	Agriculture Employment	Percent share in total Employment
HC_t	Human Capital index	Index developed by panne world table 10.1
RF_t	Average Annual Rainfall	Millimeter
FC_t	Fertilizer Consumption in (000) tons	000 Tonnes
SD	Innovative Seeds Distribution	Tonnes
INT_t	Interactive term of Human capital with Agriculture Tractors, Seed Distributions, and Fertilizers Consumptions	To Capture the Absorptive Ability

2.3. Data and Data Sources

The TFP growth of agriculture sector is accessed through time series data. The annual data were collected for the period of 1973–2020 from different sources. The secondary data were collected from domestic and foreign sources. The foreign sources consist of World Development Indicators (WDI) and Food and Agriculture Organization (FAO). Meanwhile, information from domestic sources is taken from Pakistan Meteorological Department (PMD) Pakistan Agricultural Research Council (PARC), Ministry of National Food Security & Research, Ministry of Finance Pakistan, Economic Survey of Pakistan, and Pakistan Bureau of Statistics. The secondary source data were collected from various issues of economic surveys of Pakistan, reports issued by PMD [49], and different statistical books issued by Pakistan Bureau of statistics.

3. Results and Discussion

The purpose of this research is to examine the impact of R&D adoption, climatic factors, and absorptive ability on ATFP growth. Time-series data are utilized for long-run analysis, namely, to assess trending behavior and causes of spurious analysis. To avoid spurious analysis through the data cleaning process, the problem of multicollinearity and endogeneity is detected. The problem of multicollinearity existed due to interactive terms, and for this purpose, different models are estimated through incorporating the proxies of R&D adoption. Three models are estimated to avoid the multicollinearity in the dynamic autoregressive distributive lag (ARDL) approach, while the TSLS instrumental variable technique is applied as a remedy to endogeneity problems and to investigate the behavior of coefficient cleaning in the endogeneity problem.

3.1. Agriculture TFP Growth

The calculated value of $ATFP_t$ is given in Figure 1. The estimates show positive and upward trending behavior of $ATFP_t$ in Pakistan. The average $ATFP_t$ growth remains at

1.29 percent in Pakistan from 1972 to 2020. The $ATFP_t$ growth was 1.45% in 2020, which is less than the world agriculture TFP growth that was 1.63% in 2020 [1]. To ensure food security in Pakistan, it is necessary to increase ATFP growth at least at the rate of population growth, which was 1.95% in 2020 [50]. The $ATFP_t$ growth was high from 2000 to 2008 because of government structural improvement, e.g., cemented canals, agriculture credit structure, etc. especially in Punjab, Pakistan. This was the season that the average agriculture growth remained at 4.83% from 2003 to 2008 in Pakistan [51]. During this period, the government focused on the agriculture sector in different ways, such as agriculture research, improving the water use efficiency, agriculture institutional development, and extension services to educate the farmers about agriculture innovation [23,51,52].

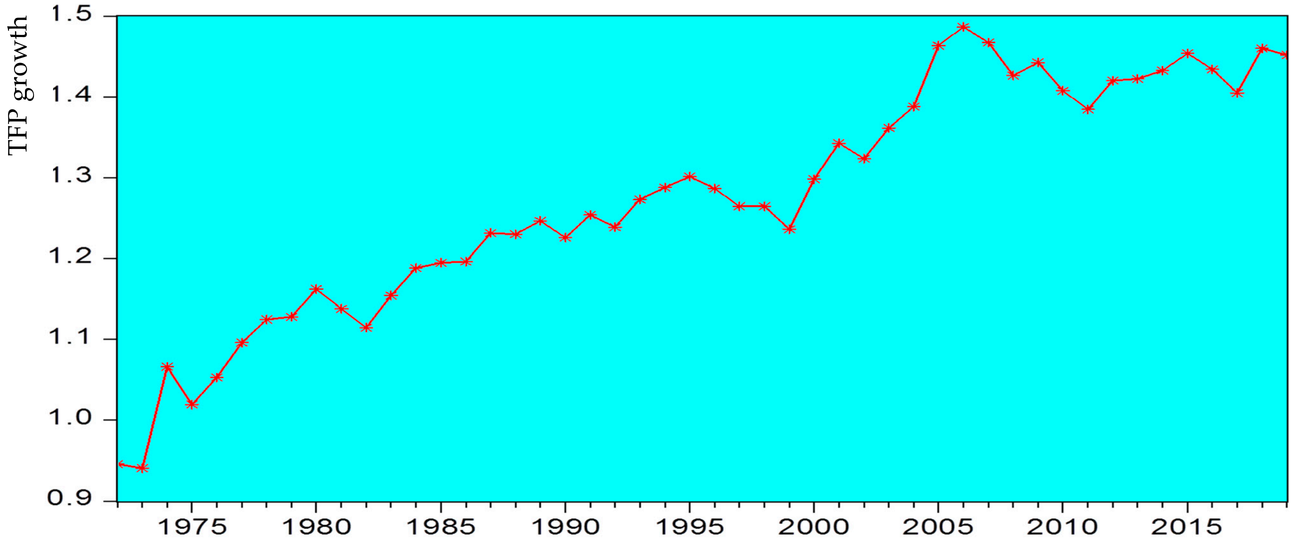

Figure 1. Agriculture Total Factor Productivity in Pakistan. Source: Author's Calculation.

3.2. Stationarity Results

In nature, time series data are used to assess trending behavior, which may cause the problem of spurious analysis. To avoid the spurious analysis, it is important in investigate the stationarity behavior. For this instance, the augmented Dickey–Fuller (ADF) unit root test is applied, and the results are given in Table 2. The ADF test findings indicate that all variables are stationary at first, except rainfall (RF_t) and agriculture land (AL_t). This clearly indicates that $ATFP_t$ growth in Pakistan is highly dependent on previous period R&D adoption, skills, and experience based human capital. Additionally, for $ATFP_t$ growth, the climatic factors and under cultivation land constitute an important matter in the present period.

Table 2. The ADF Test Results.

Variables	Level		First Difference	
	T-Stat	*p*-Value	T-Stat	*p*-Value
TFP_t	0.0060	(0.6796)	−6.1420	(0.0000) *
AL_t	2.8426	(0.0236) *	5.1769	(0.0000)
AI_t	−1.3215	(0.1693)	−3.2986	(0.0016) *
$LAEMP_t$	−1.1515	(0.6874)	−8.2817	(0.0000) *
LHC_t	−1.2886	(0.6270)	−6.6419	(0.0000) *
LRF_t	−5.4196	(0.0003) *	−5.9350	(0.0001)
LAT_t	0.0791	(0.9607)	−8.4761	(0.0000) *
SD_t	(1.3291)	(0.4932)	6.1674	(0.0000) *
$LFCT_t$	−0.1679	(0.9345)	−5.0333	(0.0002) *

* Indicates the integration level of all variables.

3.3. ARDL Estimates

The $ATFP_t$ growth of Pakistan is measured through Cobb Douglas and Translog production functions, and the estimated value of long-run analysis results are shown in Table 3. For empirical analysis, three different models are estimated to captures the role of R&D adoption and climatic sensitivity in $ATFP_t$ growth in Pakistan. The purpose of pertaining different models is to avoid multicollinearity and endogeneity challenges (results are given in Table 4. At the next stage, the endogeneity problem addressed through the TSLS method by selecting the appropriate instrumental variables. In estimated models, the dependent variable is $ATFP_t$, while independent variables are AI_t, AT_t, SD_t, FC_t, and interactive term $(INT)_t$. The INT_t is buoyed to capture the laborer absorptive ability. The other control variables are AL_t, $AEMP_t$, HC_t, and RF_t. In all three models, the calculated value of ARDL bound test is greater than the upper bound, which specifies the significant rejection of the null hypothesis of no cointegration relationship among estimated variables. The empirical results of the ARDL bound test show that all three estimated models have long run cointegration association. The percentage share of control variables AL_t, $AEMP_t$, AI_t, and RF_t in agriculture TFP growth is 26%, 8%, 19%, and 17%, respectively. The contribution of R&D adoption variables AT_t, SD_t, and FC_t to TFP growth is 28%, 24%, and 17%, respectively.

Table 3. ARDL Long Run Coefficient and Bound Test Results.

	Model 1		Model 2		Model 3	
Variables	**Coefficient**	**Prob**	**Coefficient**	**Prob**	**Coefficient**	**Prob**
C	−5.6559	0.0000 ***	3.9484	0.0276 **	−2.3173	0.0000 ***
LAL_t	0.2625	0.0188 **	0.1286	0.0292 **	0.0727	0.2535
$LAEMP_t$	0.08547	0.0921 *	0.0206	0.8421	0.1993	0.8016
LAI_t	0.1914	0.0102 **	0.0298	0.0001 ***	0.5134	0.0001 ***
LHC_t	0.2876	0.4220	0.2560	0.1934	0.0591	0.3562
LRF_t	0.0073	0.0146 **	0.0102	0.7351	0.1726	0.0008 ***
INT_t	−0.06431	0.0515 *	−0.0689	0.0066 **	−0.5887	0.0002 ***
LAT_t	0.2865	0.0086 ***				
LSD_t			0.2475	0.0282 **		
LFC_t					0.1769	0.0001 ***
ARDL Bounds Test	F-Statistic	5.1832	F-statistic	5.0530	F-statistic	16.7837

***, **, * represents the level of significance at 1, 5 and 10 percent respectively.

Table 4. Diagnostic tests results.

Endogeneity Test		**Prob-Value**
J-statistic	25.436	(0.1466)
Instrument Rank	19	
Difference in J-stats	3.4283	(0.9047)
Restricted J-statistic	31.460	
Unrestricted J-statistic	28.032	
	Autocorrelation	
Prob. Chi-Square	0.1830	
	Heteroscedasticity Test	
F-Statistic	0.0524	(0.4225)
	Normality Test	
Jarque–Bera Test	2.004	(0.367)

In model 1, the calculated value of agriculture land (AL_t) has positive and significant impact on $ATFP_t$ growth with elasticity value of 0.2625. As cultivation land is increased with other efficient input factors, the agriculture productivity will increase in long-term. The computed coefficient of AL_t shows a 1% increase in agriculture land increasing the

$ATFP_t$ by 26%. The magnitude value AL_t highlights that agriculture land holds a higher share in $ATFP_t$ growth and reduction in cultivation land reduces the agriculture productivity. Urbanization is the reason for a reduction in cultivation land and lowering of the agriculture share of GDP [53], creating food security challenges in Pakistan. The outcomes of the study are consistent with the findings of Villoria [48], who empirically found the increase in cropland area to be an agriculture productivity input to increase the $ATFP_t$ growth. Land ownership policies play a key role and land inputs made a remarkable contribution to agriculture output [54]. The coefficient value of $AEMP_t$ has a positive and significant impact on $ATFP_t$ growth in Pakistan. The $AEMP_t$ coefficient value is 0.085, which is significant at the 10% level. The calculated value of $AEMP_t$ indicates that agriculture labor has an 8% share in $ATFP_t$ growth. The $AEMP_t$ results illustrated that agriculture labor has a productive contribution to $ATFP_t$ growth, and therefore the efficient agriculture labor produces a fruitful effect on $ATFP_t$ growth. Further, the agriculture sector of Pakistan disguises unemployment, which is a reason for lower labor productivity share in agriculture output.

Agriculture investment is considered in the model to capture the as proxy of innovation adoption ratio, the result of agriculture investment (AI_t) shows significantly positive effect on $ATFP_t$ growth. The coefficient value of AI_t is 0.1914, which is significant at 5%. AI_t result indicates that one percent increase in agriculture investment increases the $ATFP_t$ growth by 19%. The positive impact of AI_t highlights that, in agriculture, investment in innovation adoption has a key contribution to agriculture output. The outcomes are consistent with the results of Ahmed & Javed [52], who argued that timely agriculture investment and innovation adoption as inputs perform a productive role in agriculture output. In addition, Aslam [55] highlights that lower agriculture investment in innovative technology represents a fundamental constraint, including advanced technology availability, institutional support, and socio-economic conditions for agriculture sector.

The variable rainfall is used as proxy of climatic sensitivity to check the effectiveness in ATFP growth. The moderate level of rainfall has a crucial role in agriculture production. The rainfall in detrimental conditions causes the climate vulnerability, which affects the agriculture production directly. The estimated value of rainfall (RF_t) has a significantly positive impact on agriculture TFP_t. This shows that effective RF_t and its proper utilization have an advantage to accelerate the $ATFP_t$ by 0.7%. The RF_t results indicate that sustainable rainfall with managerial efficiency has a positive role in agriculture productivity. Therefore, the adoption of climatic smart agriculture induces the agriculture output, which can be achieved through proper utilization and mechanism for rainwater. For better use of rainwater, the government water policies and farmers efficiency are very important. These findings are consistent with Olayide et al. [56], who argued that directly rain-fed irrigation has a limited impact on output, whereas the appropriate utilization of rainwater has a positive and long-term impact on agriculture production. The estimated result of human capital (HC_t) shows an insignificant impact, while the interactive term ($HC*AT_t$) has a negative and significant influence on $ATFP_t$ growth. The insignificant results of HC_t and negative outcome of the interactive term highlight that the agriculture labor force has less absorptive ability about technological innovation. The estimated results are similar to the findings of dos Santos et al. [57] who found that the farmers who have high absorptive ability are those who are closer to research institutions and they have higher networking, while the lower networking farmers have less absorptive ability. Similarly, Onegina et al. [58] concluded that the labor productivity in the agriculture sector is dependent on capital spent to increase the labor efficiency. The agriculture human capital will be more efficient if government focused on the knowledge capital and skill development of the agriculture labor.

To capture the impact of R&D innovation adoption on $ATFP_t$, different proxies are taken, such as agriculture tractors, innovative seed distribution, and agriculture fertilizer consumptions. The coefficient value of the agriculture tractor (AT_t) has a positive and significant effect on $ATFP_t$. The results of AT_t highlight that a 1% increase in the number of tractors in the agriculture sector increases the $ATFP_t$ by 28%. This indicated that technological adoption in agriculture performs an essential role in agriculture productivity. The estimated value of LAT_t indicates that R&D expenditure on agriculture technology performs fruitful role in enhancement of $ATFP_t$. Estimates directed that farmers should be a focus of LAT_t to increase the production efficiency and $ATFP_t$ growth. Based on outcomes, it is recommended that the farmers should focus on R&D innovation adoption to enhance their production and profitability. Additionally, the government should support the farmers to speed up the R&D innovation adoption and spillover process to enhance agriculture productivity. Similar results were found by Cavallo et al. [59] who argued that farmers with agriculture tractor adoption increase output, while the contract and large-scale farmers are more up to date in the adoption of innovations in agriculture.

In model 2, the policy variables AT_t and interactive term are replaced with innovative seed distribution variable, while taking the control variables constant. The estimated behavior of all other variables are alike to the estimated model 1, except for the minor change in magnitude of the coefficients and the RF_t variable behavior. The RF_t variable has an insignificant impact on $ATFP_t$ growth. The innovative seed distribution (SD_t) is utilized to capture the R&D innovative adoption in the agriculture sector. The coefficient value of SD_t in agriculture has a positive and significant impact on $ATFP_t$ growth in Pakistan. This illustrated that innovative seed distribution has a dynamic role in agriculture output. The estimated value of SD_t shows that a 1% increase in innovative seed adoption in agriculture increases $ATFP_t$ growth by 24%. The innovative seeds perform a crucial role in agriculture output and hybrid seed technologies are more disease secure, climatic resilient, drought resistant, etc. through which farmers can attain higher output. Similarly, Adolwa et al. [60] concluded that the agriculture productivity is low where the access to innovative seeds is low, and heterogeneity exists in seed distribution among farmers. The coefficient value of the interactive term of seeds distribution and human capital has a negative and significant impact. The negative coefficient of INT_t infers that the knowledge capital about innovative seed adoption has less absorptive ability, farmers have weak knowledge about innovative seed distribution, and its early adoption is neglected.

In model 3, the R&D innovation adoption is captured through fertilizer consumption by taking the control variables as in the first model. The coefficient value of fertilizer consumption has a positive and significant impact on $ATFP_t$ growth in Pakistan. This indicates that farmers FCt for high yield has a key contribution to increasing FC_t, optimally increasing the $ATFP_t$ by 17% annually. The findings are inconsistent with the outcomes of Raza et al. [36], who found an insignificant impact of fertilizers on agriculture output with a lower adaptive rate. The coefficient value of the interactive term of FC_t and HC_t has negative and significant impact. The negative coefficient of INT_t supports that the knowledge capital about optimal fertilizers utilization has less absorptive ability and farmers have weak knowledge to gain the actual outcome of fertilizer consumption.

The ARDL short-run estimates are given in Table 5 where the short-run coefficients have an insignificant impact on $ATFP_t$ growth in Pakistan. In all three models, the coefficient value of short-run control variables AL_t, $AEMP_t$, AI_t, HC_t, and RF_t and their lag coefficients demonstrate similar behavior as in the long run and mostly have an insignificant impact on $ATFP_t$ growth. The lag coefficient value of HC_t has a significantly positive impact on $ATFP_t$. The lag value of HC_t indicated that education with field experience positively contributes towards $ATFP_t$ growth. Additionally, the R&D innovation indicators show a positive and significant impact on $ATFP_t$ growth in the short run. In the multivariate time series model, the convergence behavior, stochastic trend, and speed of adjustment of the dependent variable are attained through the error correction model (ECM). The $ECM_t(-1)$ coefficients values in all three models are negative and statistically significant, showing that the estimated models have convergent behavior towards equilibrium. The higher value of ECM (-1) revealed that if there is a disequilibrium in R&D input, adoption and input shocks can be adjusted with higher speed during the given period. The agriculture R&D innovation inputs perform an essential role in bringing $ATFP_t$

into its steady-state position [53]. The ECM_t (−1) coefficient value is higher due to two cropping seasons (Rabi and Kharif) in Pakistan, with heterogeneously located areas, so if the production of one crop is lower, its production deficiency will recover either during the same crop or during the next crop [53,61].

Table 5. Short Run and cointegration coefficient.

Variables	Model 1 Coefficient	Model 1 Prob	Model 2 Coefficient	Model 2 Prob	Model 3 Coefficient	Model 3 Prob
D(LTFP(−1))	0.0953	0.5436	0.3232	0.6231	0.5219	0.2710
D(LAL)	0.2542	0.0494 **	0.2524	0.0917 *	−0.0702	0.2808
D(LAL(−1))	0.0437	0.7240	0.2115	0.7429	−0.0226	0.6749
D(LAEMP)	0.0409	0.1120	−0.0114	0.8399	0.0271	0.5102
D(LAEMP(−1))	0.3826	0.3411	−0.0435	0.4813	−0.1038	0.0067 ***
D(LAI)	0.0182	0.8102	−0.0002	0.9475	0.1297	0.2510
D(LAI(−1))	0.0767	0.4268	0.0147	0.0255 **	−0.0861	0.4476
D(LHC)	0.7468	0.1356	0.0142	0.0717 *	0.0106	0.3214
DLHC(−1))	0.7219	0.1317	0.0185	0.0743 *	0.0491	0.0018 ***
D(LRF)	0.0045	0.0251 **	0.0056	0.7457	0.4705	0.1002
D(LRF(−1))	−0.0015	0.2216	0.0054	0.7366	−0.6895	0.0131 **
D(INT)	−1.4814	0.1305	−0.0310	0.0684 *	−2.4624	0.0077 ***
D(INT(−1))	−1.4169	0.1264	−0.0450	0.0552 *	−0.0815	0.9539
D(LAT)	0.9725	0.3580				
D(LAT(−1))	0.4962	0.0842 ***				
D(LSD)			0.1592	0.0083 ***		
D(LSD(−1))			0.1700	0.0136 ***		
D(LFCT)					0.6958	0.3146
D(LFCT(−1))					−0.8848	0.2822
ECM (−1)	−1.2128	0.0001 ***	−0.5536	0.0019 ***	−1.1577	0.0000 ***
Autocorrelation (Breusch–Godfrey)	0.0862 (0.9176)		0.5222 (0.5983)		2.2928 (0.1376)	
Heteroskedasticity (Breusch–Pagan–Godfrey)	1.2323 (0.3035)		1.3594 (0.2341)		0.3984 (0.9840)	
Normality (Jarque–Bera)	2.6202 (0.2697)		4.3351 (0.1035)		1.8697 (0.3925)	

***, **, * represents the level of significance at 1, 5 and 10 percent respectively.

3.4. Endogeneity and Diagnostic Test Results

The variables highly correlated with error create the endogeneity problem and the chosen lag period value is used as the instrumental variable. After identifying the instrumental variables, the endogeneity test for the validation of unbiased selection instruments was applied. As the estimated variables are first order stationary, to avoid the spurious results, the endogeneity problem was initially detected through Hansen's (1982) J-test [62]. The null hypothesis of the endogeneity test is that the variables behave endogenously. The results of endogeneity test and residual diagnostic estimates are given in Table 5. The estimated result of J-stat is insignificant, which is evidence of the endogeneity problem in the estimates. Further, the selected instruments are uncorrelated with the residual term and independent variable. This selection resolves the problem of non-stationarity, heteroscedasticity, and autocorrelation in the estimated model [62,63]. To resolve the endogeneity problem, a one-year lag of highly correlated variables was used as an instrumental variable in the two stage least square (TSLS) approach [64]. Further, the interactive term is helpful in resolving the endogeneity problem. The TSLS is an instrumental variables approach, which efficiently handles the endogeneity and spurious regression problems [63]. The residual diagnostic estimates highlight that there is no evidence of heteroscedasticity and autocorrelation in the estimated model. Further, the data are normally distributed.

3.5. Two Stage Least Square Results

The results of TSLS are given in Table 6, where the dependent variable is $ATFP_t$, while independent variables are AI_t, $AEMP_t$, AT_t, SD_t, FC_t, HC_t, and interactive term (HC *AT_t). The estimated value of the F-statistic is high and significant, which shows that model is overall significant and likely useful for policy implication. The value of R-square is 0.93, which indicates that the estimated model is well-fitted, and 93% variation in $ATFP_t$ growth is explained by the selected independent variables. In general, the TSLS analysis shows that agriculture investment, agriculture land, seed distributions, tractors, fertilizer consumption, and rainfall perform a positive and significant role in $ATFP_t$. The estimated value of agriculture employment and human capital has an insignificant impact on $ATFP_t$, whereas the calculated value of the interactive term have a negative and significant impact on $ATFP_t$. The agriculture labor is less efficient in R&D innovation absorption due to over-employment and poor knowledge of R&D innovation.

Table 6. Results of Two Stage Least Square.

Variable	Coefficient	*p*-Values
C	1.8428	0.0138 **
LAI_t	0.0161	0.0005 ***
$LAEMP_t$	−0.0883	0.4002
LAL_t	0.2151	0.0173 ***
LHC_t	0.6950	0.3063
LRF_t	0.0976	0.0000 ***
INT_t	−0.0453	0.0038 ***
LAT_t	0.0731	0.0637 *
LSD_t	0.1209	0.0392 **
$LFCT_t$	0.0718	0.0189 **
F-statistic	133.126	(0.000) ***
R-squared	0.93	

***, **, * represents the level of significance at 1, 5 and 10 percent respectively.

Agriculture investment is considered as proxy of R&D capital. The result of agriculture investment (AI_t) shows significantly positive effect on agriculture productivity growth. The coefficient value of AI_t is 0.016, which is significant at 10%. This indicates that a 1% increase in agriculture investment increases the $ATFP_t$ growth by 1.6%. The positive impact of agriculture investment highlights that an increase in agriculture investment has key contribution to productivity. The outcomes are consistent with the results of Ahmed & Javed [52], who argued that timely agriculture investment and innovation adoption as inputs performs productive role in agriculture output. The estimated value of $AEMP_t$ has a negative and insignificant impact on agriculture $ATFP_t$. The insignificant impact on $AEMP_t$ on agriculture productivity may be due to overemployment in the agriculture sector. Similarly, Onegina et al. [58] concluded that the labor productivity in the agriculture sector is dependent on capital spent for increasing the labor efficiency.

The variable rainfall is used as proxy of climatic sensitivity, as a moderate level of rainfall has a crucial role in agriculture production. The rainfall in detrimental condition caused climate vulnerability, which directly affects the agriculture production. The estimated value of rainfall (RF_t) has a significantly positive impact on $ATFP_t$. This shows that effective RF_t and proper utilization of rainwater led to more accelerated agriculture productivity by 9.7%. The RF_t results indicate that sustainable rainfall with managerial efforts has a positive role in agriculture productivity. Therefore, the adoption of climatic smart agriculture induces the agriculture output, which can be achieved through proper utilization of rainwater. For the better use of rainwater, the government water policies and farmer efficiency are very important. The findings are consistent with Olayide et al. [56], who argued that directly rain-fed irrigation has a limited impact on output, whereas the appropriate utilization of rainwater has a positive and long-term impact on agriculture production.

The coefficient value of the agriculture tractor (AT_t) is positive and significant. The AT_t results highlight that a one percent increase in the number of tractors in agriculture sector increase the $ATFP_t$ by 7.3% in Pakistan. This indicated that technological adoption in the agriculture sector of Pakistan performs an essential role in agriculture productivity. As a result, the farmers should focus on innovation adoption to enhance their production and profitability. The farmers' technological adoption behavior speeds up the spillover process and agriculture output. Similar results were found by Cavallo et al. [59] who argued that farmers' agriculture tractors adoption behavior increases the spillover impact, while the contract and large-scale farmers are more up to date in their adoption of innovation in agriculture. The coefficient value of SD_t in agriculture has a positive and significant impact on $ATFP_t$ growth in Pakistan. The estimated value of SD_t shows that one percent increase in innovative seed in agriculture leads to increase the $ATFP_t$ growth by 12 percent. The innovative seeds perform a crucial role in agriculture output and crops are more disease protected, climatic resilient, drought resistant, etc. through which farmers can attain higher output. Similarly, Adolwa et al. [60] concluded that the agriculture productivity in those areas where there is access to innovative seeds is low, and heterogeneity exists in seed distribution among farmers. The coefficient value of fertilizer consumption has a significant impact on $ATFP_t$ growth in Pakistan. This indicates that farmers are willing to adopt the fertilizers for higher agriculture output. The findings are consistent with the outcomes of Raza et al. [36], who found significant fertilizers impact on agriculture output.

The estimated result of human capital (HC_t) presents a insignificant and positive effect, while the interactive term ($HC{*}AT_t$) shows significant and negative effect on $ATFP_t$ growth. The insignificant results of HC_t and negative coefficient of the interactive term highlights that agriculture labor has weak knowledge capital with lower R&D absorptive ability. The results indicate that agriculture labor has less absorptive efficiency of innovative technology at an early stage. The estimated results are similar to the findings of dos Santos et al. [57] who found that farmers have high absorptive ability those who are closer to research institutions have higher networking, while the lower networking farmers have less absorptive ability. Onegina et al. [58] concluded that the government needs to focus on agriculture knowledge capital, extension services to enhance the knowledge spillover in agriculture, educate the farmers about earlier innovation adoption, and increase the absorptive ability to gain high productivity. Farmer expertise, knowledge capital, and best practices for technology absorption have an effective role to play in agricultural development in Pakistan.

The authors in this study have used the time series data from 1973–2020 to assess the impact of R&D on agricultural productivity growth in Pakistan. Authors had data limitations as is true with many studies based on time series data. Meanwhile, these data can also be split into two different periods (1973–2000 and 2001–2020) to investigate the structural difference. The use of a structural break in data analysis can be more beneficial to determine structural differences and investigate the before and after shocks of R&D. However, the limited number of observations, 28 and 20, respectively, in the time series data available for two structural breaks (1973–2000 and 2001–2020) may create the spurious analysis problem as a normal distribution assumption may not hold and it may mislead the analysis of structural difference and make the test invalid.

4. Conclusions and Recommendations

This study investigates the role of R&D adoption in agriculture TFP growth in Pakistan. For the empirical analysis, the annual time series data were collected spanning from 1973 to 2020. The problem of multicollinearity existed due to interactive terms, and for this purpose, different models were estimated through incorporating the proxies of the R&D innovation adoption. Three models are estimated to avoid the multicollinearity in the dynamic ARDL approach, while the TSLS instrumental variables technique is applied as a remedy to the endogeneity problems and to investigate the behavior of the estimated coefficient cleaned from the endogeneity problem. It can be concluded from the analysis results that R&D adoption presents a fruitful impact on agriculture TFP growth in Pakistan. Agriculture innovation adoption spending, seed distribution, fertilizer consumptions, and agriculture tractors each perform a positive role in agriculture TFP growth. This indicates that the adoption of agricultural R&D innovation is a fundamental source of higher agriculture productivity. However, the human capital and agriculture employment show insignificant results, while interactive terms indicate a negative and significant impact on agriculture TFP in Pakistan. This highlights that the agriculture labor force has less innovation adoption knowledge and absorptive ability for R&D innovative in agriculture sector of Pakistan. The results indicate that sustained rainfall with managerial efforts play a productive role in agriculture productivity. Consequently, the adoption of climate smart agriculture induces higher agriculture output, which can be achieved through the proper utilization of rainwater. To improve agricultural output and farmers' absorptive ability, the following policy measures are required:

1. The government and research institutions should increase the agriculture R&D innovation expenditures to increase agriculture productivity.
2. The research institutions and government should focus on innovative seed development (like hybrid seeds) and its early spillovers for higher agriculture productivity.
3. Urbanization has caused a reduction in cultivation land and lowered the agriculture output. So, the government should focus to enhance the under-cultivation of land to avoid food security challenges in Pakistan.
4. The government must develop and implement the extension services to educate the farmers about technological innovation and efficient resource utilization.
5. The government and technology developing agencies should focus on farmers' expertise, knowledge-based training, skills-based workshops, capacity building, and community-led experiences to improve the absorptive ability of new technology.
6. Farmers should also focus on the adoption of climate smart agriculture, which can be achieved through a proper utilization of rainwater. For this purpose, the government needs to develop small community dams and large-scale dams for the timely use of rainwater.

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