The relationship between staple food crops consumption and its impact on total factor productivity: does green economy matter?

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Abstract
The agriculture sector is a key driver of economic growth and provides employment opportunities across the globe generally. However, in today’s world, agricultural product demand is more influenced by taste, prices, and nutritional value due to climatic variation. The study has analyzed the current situation grain productivity by using the data of farm inputs and major grain crops of Pakistan from (1960–2020). The study consists of a two-stage analysis in the first stage, the total factor productivity (TFP) variable is obtained by using the parametric Tornqvist-Theil index output-input-aggregation method separately for each crop; rice, maize, and wheat. After that, the unit root test is used to check the stationarity and trend of the variables in the long run. Subsequently, the autoregressive distributed lag (ARDL) model is applied to check the existence of cointegration in the long run and short run among the variables. The results of the study disclosed that the consumption of rice has a positive relationship with its total factor productivity, but, wheat and maize have a negative long-run cointegration relationship with the respective productivities. The study results have shown that the consumption pattern of staple crops has substantially changed, due to climatic variation, and the current food consumption trend is revealing new dimensions and trends owing to variation in climate change and anthropogenic pressure which demands to adapt climate resilient farm practices.

Keywords Economic growth · Agriculture sector · Green revolution · Total factor productivity · Tornqvist-Theil index · ARDL

JEL Classifications Q11. Q13. Q16. Q18

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Introduction

The agriculture sector across the globe generally, and particularly in Pakistan, is in a transitional phase. In today's world, agricultural product demand is more influenced by taste, price, nutritional value, accessibility, and climatic variation compared to the past. Since, the contemporary world is more concerned about environmental cost, food sustainability, energy connections, and locavers voices. For this reason, farmers weight each factor such as local market conditions, consumers' demand, farm input prices, and the intensity of urbanization into account, since, peripheral areas of urban centers have turned into small markets. However, scarcity is a paradox which is undermining previously achieved remarkable achievement of food surplus and self-sufficiency and it is increase in grain crops' prices in the world supermarkets (Benton and Bailey (2019)). For this reason, consumption of higher-value food like meat and dairy products across all income levels has increased (Arslan et al. 2021; Arslan et al. 2021; Chen et al. 2022; Cao et al. 2022; Dai et al. 2022; Shabbir and Wisdom 2020; Liu et al. 2022b). However, these changes are not equal across the regions of the world, because the calorie intake has remained stagnant in Africa and South Asia. Similarly, Pakistan’s agriculture sector is facing daunting challenges, due to the massive increase in population dependence per hectare, so, the per capita land availability for to grow food has decreased in the country, and productivity is stalled. Major grain crops (wheat, rice, and maize) grow less than 1% annually, which is lower than the population growth of Pakistan (2.4) (2018–2019 economic survey of Pakistan). The reason is that macroeconomics approaches in Pakistan are not promising, besides discontinuity in the policies has harmed the poor population of the country (Chandio et al. 2020).

The objective of the study is to find the relationship between staple/grain crops' yield kg per hectare productivity with their respective farm inputs1, asides from finding the trend that what current total factor productivity pattern is revealing, in the context of farm inputs.

The subsequent sections of the study are organized in this way: the first section consists of the overview of Pakistan grain consumption pattern, and “Literature review” section is about the literature review. “Data and methodology” section deals with methodology and a detailed description of the variables used in the study. “Empirical analysis/results/discussion” section contains the result of ADF, bound test, and ARDL: autoregressive distributed lagged model, in the last, we have concluded the study.

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1 Since total factor productivity is an index approach which takes in to account output: quantity and prices. Input prices and quantities for each year to calculate TFP.

Literature review

The literature review of the study is divided into three sections because agricultural productivity growth is referred to as a shift in the aggregate agricultural production function. A literature review about Pakistan shows that, after wizarat (Wizarat 1981), results explored high yield variety seeds, water availability, and machinery are the real game-changer.

Yahya et al. (2013) explore that in Pakistani society, consumption trend of fast food is increasing. For this study, SPSS descriptive inferential analysis was used to get the results. Ahmed et al. (2017) study also acknowledged that in recent years, dining out trend has increased substantially. The trend is on the incessant rise in Pakistan and it is indicating the variation in the lifestyle of people of Pakistan that how eating habits are changing and directly hitting the crop productivity. Chandio et al. (2018) employed the ARDL long-run cointegration approach to investigate the short-run and long-run determinants of grain crop productivity in Pakistan (1978–2016). Results disclosed that modern farm inputs are a real game-changer. However, farm size has decreased in Pakistan and most of the farmers have a small tract of land, and they are not able to purchase heavy and expensive machinery. So, this contributes to a little decrease in yield kg per hectare.

For this reason, crop productivity is directly proportional to food consumption. The study revealed that there is a negative relationship between market production and the calorie of rice intake per capita. The farmers have to maintain the objective of agriculture sustainability, since, climate change is hitting the world hard, and trade patterns are following climatic patterns (Benton and Bailey 2019).

Shujaat Abbas (2020) investigated the relationship between climatic variations and total cropped area under cultivation of cotton across Pakistan. In the study, the data from 1980 to 2018 has been used for ARDL regression analysis. The prime objective of the study was to find the causal and long-run relationship exists between climatic variables and farm inputs. The results significantly proved that if temperature increases, it adversely affects crop production, for this reason, fertilizers demand accelerated and its consumption per hectare increases since the variable has shown a positive and significant trend with the crop productivity in the short run and long run.

Chandio et al. (2021) are the first recent effort that assesses the long-term impact of climatic variation on agriculture production in South Asian countries. The data over the years 1991 to 2016 is used in the study to regress the penal dynamic least square (PD-LS) method, besides various co-integration techniques to check robust cross-sectional dependence besides slop heterogeneity. The results
explore that there is long-term co-integration exists among the variables, because climatic variation significantly affects crop production negatively in the long term, and an increase in carbon emission reduces productivity substantially. Whereas, precipitation increases crop production in the long run and short run both. Moreover, other farm and non-farm variables also play their critical and significant role.

Mahdavian et al. (2022) estimated the asymmetric relationship between climatic variation impact on agricultural food production by taking into account all of the geospatial variables and farm inputs by using the NARDL and granger causality test on the data over the years 1961 to 2019. The results explore that energy consumption has negative effects on farm production if sources of energy generation emit more greenhouse gas emissions. Subsequently, the farmers are compelled to use a higher ratio of fertilizer consumption kg per hectare. Furthermore, the “Literature review,” for instance, (Sadiq et al. 2022; Saleem et al. 2022; Yaqoob et al. 2022; Yikun et al. 2021) have shown that various studies have used ARDL: autoregressive distribution lag model to analyze the effect of climatic stress and population pressure, which is the prime cause of the increase in cost and variation in farm output prices, besides its impact on land use impact and eventually on-farm productivity.

**Theoretical framework**

The conceptual and theoretical framework of the study is drawn from Benton and Bailey (2019) study which addresses the severity of climatic crises on farm income and productivity in given circumstances. By reviewing the literature, it has been found that total factor productivity is an index of technical progress which gives an idea of factor use efficiency over the time, because it uses the output per unit combination of capital and labor. The TFP indices work well with the known conceptual and estimation intricacies that involve many highly restrictive assumptions. These included a constant return to scale and competitive static equilibrium, and the concept which was used in the studies of Kendrick (1956) and Solow’s (Robert Solow 1957) agriculture growth model. The functional form of the model is given under Eq. no. 1.

\[ Y = F(K, L, A, t) \tag{1} \]

\[ Y \quad \text{aggregate output.} \]

\[ K \quad \text{available overall capital inputs in a sector (machinery, and equipment)} \]

\[ L \quad \text{aggregate labor inputs.} \]

\[ A \quad \text{area of the crop (land area)} \]

\[ t \quad \text{time (it is included in the production function for the change of time)} \]

\[ Y = A(t) \ast F(K, L) \tag{2} \]

Equation (1) shows the functional relationship between output and input variables: output (yield kg per hectare) depends on (land and labor use in time t), and Eq. (2) shows how the time phenomena impact the endogenous growth in capital and labor. In a nutshell, A(t) shows growth over the periods, and innovation (technological improvement) or exogenous changes effects inputs growth.

**Data and methodology**

Pesaran and Shin (1999, 2001) introduced the autoregressive distributive lag (ARDL) model and bound test. Two of the studies acknowledged that ARDL is the most flexible econometric method particularly if we are studying the regime shift or structural changes. ARDL can host time lag and generate data process mechanisms. Particularly, when the objective is to find the long-term relationship between the dependent and independent variables which are under consideration, the autoregressive distributed lag (ARDL) cointegration technique is the best method, because, the ARDL approach is more consistent for both large and small sample data sets. Although ARDL does not require a unit root test pretest, it is preferable when the study is dealing with the variables which are integrated of different levels I(0) and I(1) or are the combination of both simultaneously. The prime benefit of this approach is that it can identify the presence of vector cointegration if there are multiple vectors. However, the techniques cannot be used if there is an order I(2) stochastics integrated trend. For this reason, in this study, the unit root test is employed before applying the ARDL cointegration technique (Nokora and Uko 2016). Furthermore, the ARDL method provides neutral estimates and validates t-statistics, and auto lag selection eliminates the correlation of the residuals, resultantly the endogeneity problem being almost wiped out, besides it requires a single form of the equation, compared to another system that requires so many equations (Ali et al. 2017).
Tornqvist-Theil index method

The total factor productivity is a multifactor productivity measure that is used for the measurement of productivity, aside it is also a determinant of technical efficiency. The Tornqvist-Theil index has distinction and it is a superlative index compared to Paasche, lespayer, and Malmquist index, since it weights each factor of production and their respective prices (Jurun et al. 2013; Khan and Rehman 2022; Olagunju et al. 2022).

In addition to output and its prices by using the data over the years (1971–2008) for the estimation of TFP. Sheng et al. (2020) applied the input-output method to calculate total factor productivity for China’s crop and livestock sector by using the gross output model-based data from 1978 to 2016. The results explore that by the year 2009, the agriculture productivity growth of major commodities in the country was 2.4%, but after 2009, the average growth rate of the commodities has decreased. Similarly, Habib and Spiegal (1994) developed an input-output index, by using farm inputs and output data to develop an index to estimate the results of total factor productivity for each crop separately.

Therefore, in this study, total factor variable is generated for each staple crop (wheat, rice, and maize) as a dependent variable by using Tornqvist-Theil index approach which has proximity to the widely used divisia index in economics for the estimation of TFP (Ali 2004).

\[
LnTfp = \frac{1}{2}(r_{it} + r_{it-1})Ln(y_{it}/y_{it-1}) - \frac{1}{2}(s_{it} + s_{it-1})Ln(x_{it}/x_{it-1})
\]  

Where \( r_{it} \) is the share of output \( i \) in the total revenue in \( t \) time, \( y_{it} \) is the output \( i \), in \( t \) time, \( S_{it} \) is the share of input \( i \) in total input cost in time \( t \), \( x_{it} \) in input \( i \), in \( t \) time. The total factor productivity is measured for each year growth formula which is employed in the study to get results.

Description of the variables

Independent variable: TFP = f (Cons (W, R, M), IC, IT, Edu, Lf, Ln T, IS, Elect, Fert).

The period of the study is from 1960 to 2020.

Dependent variable

TFP: total factor productivity obtained by using Tornqvist-Theil index output-input method.

Explanatory variables/dependent variables

- Cons: domestic consumption of the crop in million tons.
- IC: area irrigated by canal water.
- IT: area irrigated by tube well water.
- lnT: number of the tractor in millions available in the country.
- IS: high yield variety seeds consumption for each crop in million tons.
- Edu: expenditure on education as per GDP ratio.
- Fert: consumption of fertilizer in kg per hectare.
- Lf: labor employed in the agriculture sector in million.
- Elect: the consumption of electricity in the agriculture sector.
- Eit: error term

ARDL two-stage analysis has been employed in this study, at the first stage, the total factor productivity variable by using the parametric Tornqvist-Theil index output-input method is calculated for each staple/grain crop (Ramasundaram et al. 2001). In the second stage, stationarity was checked by using the augmented Dickey-Fuller (ADF), unit root test results at the level I(0), and first-order(I) and subsequently, ARDL bound test which is consist of two stages at the first long-run relationship among the variable is determined. So, if it exists and is detected, then the long-term and short-term causal relationship is estimated at the second stage within the frame of reference of error correction term (ECT). The study has adapted the (Hulten and Isaksson 2007; Yaqoob et al. 2022; Zhoumu Yang et al. 2022) general form of equation cointegration regression technique to explore the impact of technological advancement on productivity. The model form of the equation is presented given below in Eq. no. 5.

\[
TFP_{ti} = a1Cons_{ti} + a2IC_{ti} + a3 IT_{ti} + a4bTTr_{ti} + a5IS_{ti} + a6 Edu_{ti} + a7Fert_{ti} + a8ftri + a9 Elect_{ti} + \varepsilon_{ti}
\]  

(4)
ΔTFP_{it} = \alpha_0 + \sum_{j=1}^{1} \Delta TFP_{it-j} + \sum_{j=1}^{1} \Delta \text{SC}_{it-j} + \sum_{j=1}^{1} \Delta \text{Y}_{it-j} + \sum_{j=1}^{1} \Delta \ln t_{it-j} \\
+ \sum_{j=1}^{1} \Delta \text{FERT}_{it-j} + \sum_{j=1}^{1} \Delta \text{FERT}_{it-j} + \sum_{j=1}^{1} \Delta \text{ECT}_{it-j} + \varepsilon_{it} \tag{5}

\alpha_1, 2.3, 4.5, 6, 7, 8, 9 are long-run parameters in the above-mentioned Eq. no. 4, whereas, Eq. no. 5 included the \beta^0 which is the drift component, whereas, \Theta, \pi, \tau, \gamma, \delta, \omega, \tau, \text{ and } \varepsilon are short-run parameters. Besides “i” for Ith crop and t for time phenomenon.

ECTi, t is the error term and it shows convergence from short run to long run and its value must be between 0 and 1; however, some studies suggest it can be between -1 and -2, (Narayan and Smyth 2006).

**Unit root test**

In time-series data, it is a prerequisite to check the stationarity of the variables in the long run, since the bound test cannot be employed if the variables are stationary at their second order and above (Pesaran and Shin 1998; Pesaran and Shin 1995). Thereby, in this study, augmented Dickey-Fuller (ADF) unit root test is used to check the stationarity of the variables in the long run because it provides multiple options for the estimation; there is a wide range of unit root tests, but ADF (augmented Dickey-Fuller, 1979) is used in this study because the test is based on the first-order autoregressive process.

\[ TFP_{it} = \alpha_0 + \varepsilon_{it} \tag{6} \]

Whereas H_0 ≠ H_1

\[ H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = 1 \text{ (Not Stationary, No Cointegration)} \]

\[ H_1 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = 1 \text{ (Stationary, Cointegration)} \]

**Empirical analysis/results/discussion**

In this study, at the very first, the unit root test is applied to check the existence of the long-run cointegration relationship between TFP of the grain crops (wheat, rice, maize) and their given explanatory regressor besides the level of their stationarity. The results are shown in the table given below in Table 1.

**Unit root test**

The values of the ADF unit root test results are at the level and their first difference. The results of the table explore that most of the series are stationary at their level and some are at their first difference.

Total factor productivity of wheat (TFPW), rice (TFPR), and maize (TFPM), area irrigated by canal water (IC), and tubewell water (IT), besides growth in tractors (LNTR), electricity consumption in the agriculture sector (ELECT), and agriculture labor force in millions (LF) all are stationary at their level. However, domestic consumption of the grain wheat (CONSW), rice (CONSR), maize (CONSM) crops in 000 metric tons, high yield variety seeds (IMPSED), fertilizer consumption in kg per hectare (FERT), and education expenditure of government as per GDP ratio (EDU) is stationary at their first difference. Before the study, various studies (Wen et al. 2022; G., Khan et al. 2021; Bano et al. 2021; Wang 2022; Khan and Khan 2018; Gebremariam and Ying 2022) proved that when some variables are stationary at their level and some are at first difference ARDL; auto regressive distributed lag model is the best modeling tool to find the long-run cointegration relationship among the variables.

**Bound test**

To calculate the values of the bound test, it is necessary to select an optima lag-length criteria based on Akaike information (AIC), Schwarz Bayesian criteria (SBC), and Hannan Quinn (HQ). For this study based on Akaike information criteria (AIC), the minimum lag length model criteria were selected, since it has a minimum error (Albahli and Yar 2022; Romadhon and Tulalo 2022).

The above-given Table 2 depicts the results of the bound test f-statistics. The results of the bound test show that computed values of F-statistics are higher than their
critical lower and upper bound values of Akaike information criteria (AIC). This discloses that long-run cointegration relationships among the variables exist and all the series are stationary. So, it can be concluded that the ARDL model is the best-fitted model for the regression analysis of the study.

The above-given results in Table 3 describe that domestic consumption of rice has a positive and significant relationship with its productivity (TFPr), whereas maize and wheat coefficients are showing a negative relationship with total factor productivity of crop, besides being significant. Irrigation by canal water, growth in tractors, and improve seeds are showing negative relationships concerning the total factor productivity of wheat. Maize is normally grown in the Rabi season when the climatic condition does not affect the crop yield in general (Coomes et al. 2019; Mafizurrahma and Abulkashem 2017). However, the TFPpm per hectare is showing a negative relationship with the area irrigated by canal water and growth in the tractor. If the area irrigated by canal water shows a declining trend in total factor productivity of the crops (wheat and maize), this depicts, that if more area is brought under canal irrigation, the less water is available per hectare of the cropland due to intensive farm inputs use (Alemu et al. 2017). The results of the variables are significant and within the given range of primarily discussed studies concerning to speed of adjustment (Villoria 2019; Sunge and Ngepah 2020).

The above-given Table 4 shows the vector error correction model or short-run cointegration results among the variables. It means that farmers rely on recent farm input and output prevailing prices. So consumption gets affected in the short run due to fluctuation in crop supply. The availability of tractors is also dependent upon the previous season’s number of tractors available in the economy. In epitome, short-run values are more or less similar to the long cointegration coefficient values (Alhassan 2021; Akber 2022).

Table 5 shows that lag values are selected based on LR, FPE AIC, SC, and HQ autoslected criteria. Akaike’s information criteria (AIC) and Schwarz Bayesian criteria (SBC) also determine the ARDL log length criteria. In ARDL for short-run analysis, VECM3 has an advantage in that it explores the value of the speed of adjustment among the variables from the short run to the long run (Tufail and Ahmed 2015).

Table 6 depicts the goodness of the fit of the model; it is the best-fitted model since $R^2$ is a basic matrix that shows how
much variance has been explained by the model. Whereas, adjusted $R^2$ shows how the model is best and well fitted, as adjusted $R^2$ does not depend on the inclusion and exclusion of the variable in the model, but it penalized the model for not adding further irrelevant variables. The above-given model shows that for wheat ($R^2 = 0.949846$), (adjusted $R^2 = 0.885064$) for rice ($R^2 = 0.994484$), (adjusted $R^2 = 0.962076$) and maize is ($R^2 = 0.902305$), (adjusted $R2 = 0.841964$).

### Table 4 Vector error correction model

| Variable               | Wheat          | Rice           | Maize          |
|------------------------|----------------|----------------|----------------|
| D(TFPW.R,M(-1))        | 0.39 (3.40) 0.002*** | 0.77 (8.61) 0.000*** | _             |
| D(CONS(W,R,M))         | 0.00 (0.905) 0.12 | 0.00 (0.44) 0.67 | 9e-05(7.049)6e-01 |
| D(CONS(W,R,M(-1)))     | 0.00 (4.25) 0.00*** | 6e-04(4e+00)2e-04 |               |
| D(EDU)                 | 0.20 (0.090) 1.75 | 0.29 (1.79) 0.08* | 2e-02(1e-01)9e-01 |
| D(EDU(-1))             | −0.27 (−2.46) 0.019* |               |               |
| D(ELECT)               | −0.01 (0.51) 0.616 |               |               |
| D(ELECT(-1))           | −0.07 (−2.58) 0.015 |               |               |
| D(FERT)                | 0.00 (−2.20) 0.035* | 0.00 (0.12) 0.19 | 7e-04(2e+00)6e-02 |
| D(FERT(-1))            |               | 0.00 (7.23) 0.000*** |               |
| D(IC)                  | −0.06 (−1.68) 0.103 | −0.10 (1.42) 0.17 |               |
| D(IC(-1))              | 0.11 (5.25) 0.000*** |               |               |
| D(ISC)                 | −0.00 (−4.36) 0.000*** | 0.01 (4.94) 0.00 | −2e-03(2e+00)7e-02 |
| D(ISC(-1))             | 0.01 (0.24) 0.000*** | 0.00 (2.86) 0.01** |               |
| D(LF)                  | 0.07 (2.22) 0.033* | −0.22 (−4.97) 0.000*** | 2e-01(8e+00)0e+00 |
| D(LNTR)                | −0.26 (−2.16) 0.038* | 0.05 (2.18) 0.04 | 4e-01(1e+00)2e-01 |
| D(LNTR(-1))            |               | 1e+00(3e+00)3e-03 |               |
| D(TW)                  | −0.02 (−0.25) 0.805 | 0.25 (1.6122) 0.12 | 2e-02(2e+00)5e-02 |
| D(TW(-1))              | 0.00 (0.03) 0.98 |               |               |
| D(TW(-2))              | 0.70 (6.85) 0.000*** |               |               |

$t$ values are in parenthesis. Significance level is at $10\%$ (0.1)*, $5\%$ (0.5)**, $1\%$ (0.01)**

### Table 5 VAR lag order selection model

| Wheat | LogL | LR  | FPE  | AIC   | SC    | HQ    |
|-------|------|-----|------|-------|-------|-------|
| 0     | −1234| NA  | 9.35e+10 | 45.12597 | 45.38145 | 45.22477 |
| 1     | −881 | 603.2755* | 1500856.* | 34.07214 | 36.11597* | 34.86250* |
| 2     | −842 | 56.40178 | 2368819. | 34.44391 | 38.27609 | 35.92585 |
| 3     | −807 | 42.42369 | 4906692. | 34.94016 | 40.56070 | 37.11367 |
| 4     | −763 | 41.57658 | 9674153. | 35.12288 | 42.53177 | 37.98796 |
| 5     | −684 | 54.43321 | 8675074. | 34.03980* | 43.23703 | 37.59644 |

| Rice   | LogL | LR  | FPE  | AIC   | SC    | HQ    |
|--------|------|-----|------|-------|-------|-------|
| 0      | −1239| NA  | 1.82e+08 | 44.56278 | 44.88829 | 44.68998 |
| 1      | −781 | 751.6767 | 272.8117 | 31.11484 | 34.36987* | 32.37681* |
| 2      | −723 | 77.15122 | 760.2331 | 31.92253 | 38.10709 | 34.32027 |
| 3      | −639 | 83.38336 | 1318.206 | 31.83741 | 40.95149 | 35.37092 |
| 4      | −453 | 126.4209* | 139.2441* | 28.07653* | 40.00914 | 32.04124 |
| 5      | −279 | 70.64127 | 16.95773* | 22.05869* | 34.02969 | 26.68797 |

| Maize  | LogL | LR  | FPE  | AIC   | SC    | HQ    |
|--------|------|-----|------|-------|-------|-------|
| 0      | −1056| NA  | 8708088. | 38.68275 | 38.97472 | 38.79566 |
| 1      | −632 | 709.6189 | 18.25169 | 25.58352 | 28.21130* | 26.59971* |
| 2      | −577 | 61.80447 | 42.45864 | 26.28436 | 31.24795 | 28.20382 |
| 3      | −527 | 65.76909 | 72.98266 | 26.41933 | 33.71873 | 29.24207 |
| 4      | −417 | 87.32649* | 35.32380 | 24.77722 | 34.41242 | 28.50323 |
| 5      | −279 | 70.64127 | 16.95773* | 22.05869* | 34.02969 | 26.68797 |
Table 6 The goodness of fit (model summary)

| Test statistics       | Wheat  | Rice   | Maize  |
|-----------------------|--------|--------|--------|
| R-squared             | 0.949846 | 0.994484 | 0.902305 |
| Adjusted R-squared    | 0.885064 | 0.962076 | 0.841964 |
| S.E. of regression    | 0.125272 | 0.183617 | 0.192082 |
| Sum squared residual  | 0.376636 | 0.269722 | 1.254444 |
| Log-likelihood        | 60.59062 | 69.93945 | 26.9019 |
| F-statistic           | 14.66213 | 30.6869 | 14.95347 |
| Prob(F-statistic)     | 0       | 0.000014 | 0      |
| Mean dependent var    | −0.1124 | −0.20818 | −0.13403 |
| S.D. dependent var    | 0.36951 | 0.942885 | 0.48318 |
| Akaike info criterion | −1.02109 | −0.78355 | −0.17507 |
| Schwarz criterion     | 0.13625 | 0.952464 | 0.620606 |
| Hannan-Quinn criter.  | −0.57239 | −0.1105 | 0.133413 |
| Durbin-Watson stat    | 2.265605 | 2.838882 | 2.441887 |

Conclusion

Since the green revolution’s impact for long has been leveled off, consequently, wheat and maize consumption is declined, but, for rice, it is still positive due to rapid urbanization and diversification in food consumption. Currently, climate variation and crop prices have taken the eminent position in the choice of food basket, thereby, rich carbohydrate grain food per capita consumption has decreased. Other than consumption of the crop, farm input results indicate that return to scale is still only positive in terms of rice, whereas in terms of wheat and maize because of decline in land area, their productivity is decreasing.

So, it can be concluded that even though urban sprawl, putting an immense upward pressure on the domestic grain market through farm input prices. But still, by adapting multiple cropping on fragmented farm lands and by using short cropping seasons, crops output per season can be increased. Subsequently, it will improve cereal food intake per capita but for this new and innovative cereal crop production tools and techniques are required to inject new life into the agriculture sector. COVID-19 also unveiled that the short-run supply and demand gap also affects the food consumption pattern and so agriculture policies must be formulated based on disaster and risk resilience approaches as well. Log length is selected based on (AIC) and (SIC) criteria. However, the farm inputs are shown mixed responses concerning the total factor productivity of the crops, but from these results, it can be concluded that time is ripening to enter into a new and advanced phase of the green revolution in Pakistan.

Author contribution Miss Nusrat Yaqoob has completed the data analysis part, Dr Vipin completed the Introduction section, Dr Zeeshan completed the Literature review section, Dr Sharma wrote Methodology section, Dr Shabbir interpreted the data analysis section, Dr Carlos wrote conclusion, and Dr. Mosab wrote abstract parts and format the paper as per journal requirements.

Data Availability The data is available on request from corresponding author.

Declarations

Ethics approval and consent to participate This study did not use any kind of human participants or human data, which require any kind of approval.

Consent for publication Our study did not use any kind of individual data such as video, images, etc.

Competing interests The authors declare no competing interests.

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