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Effect of climate change on fruit by co-integration and machine learning

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Abstract

Purpose – The purpose of this paper is to assess the impacts on production of five fruit crops from 1961 to 2018 of energy use, CO_2 emissions, farming areas and the labor force in China.

Design/methodology/approach – This analysis applied the autoregressive distributed lag-bound testing (ARDL) approach, Granger causality method and Johansen co-integration test to predict long-term co-integration and relation between variables. Four machine learning methods are used for prediction of the accuracy of climate effect on fruit production.

Findings – The Johansen test findings have shown that the fruit crop growth, energy use, CO_2 emissions, harvested land and labor force have a long-term co-integration relation. The outcome of the long-term use of CO_2 emission and rural population has a negative influence on fruit crops. The energy consumption, harvested area, total fruit yield and agriculture labor force have a positive influence on six fruit crops. The long-run relationships reveal that a 1% increase in rural population and CO_2 will decrease fruit crop production by −0.59 and −1.97. The energy consumption, fruit harvested area, total fruit yield and agriculture labor force will increase fruit crop production by 0.17%, 1.52%, 1.80% and 4.33%, respectively. Furthermore, uni-directional causality is correlated with the growth of fruit crops and energy consumption. Also, the results indicate that the bi-directional causality impact varies from CO_2 emissions to agricultural areas to fruit crops.

Originality/value – This study also fills the literature gap in implementing ARDL for agricultural fruits of China, used machine learning methods to examine the impact of climate change and to explore this important issue.

Keywords China, CO_2 emissions, Machine learning, Co-integration, Fruit production

Paper type Research paper

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1. Introduction

The magnitude of impacts on agricultural systems typically fluctuates according to geographic factors. China is one of the largest centers of farmed plant origin in the world. Today China is inherent in several deciduous fruits, such as apples, bananas, citrus, pears and grapes. The impacts of climate change on-farm yields in various parts of the world have been explored in economic literature (Chandio *et al.*, 2020). There have been several previous studies on agriculture. Liu *et al.* (2015) describe the importance of vegetation, the effects of climate changes on vegetation growth.

Ahsan *et al.* (2020) discuss the impact on the production of cereal crops in Pakistan of CO_2, energy usage, labor and cultivated area. The study reveals the comparison of vegetation growth in different climates and also shows increasing and decreasing vegetation depending upon climate trends or dominancy. Chen *et al.* (2003) explain the natural vegetation, effects of climate change on different zones in China. There have been several previous studies on agriculture. The relationship of vegetation with climate changes and vegetation growth in different zones is presented by Weng and Zhou (2006). The interaction of climate and the vegetation and the classification of climate and vegetation which helps to develop strategies for increasing growth and food security in China (Zhou and Wang, 2000). Xu *et al.* (2016) explain the climate changing, heat variations and influence of thermal variations on the natural ecosystem, different vulnerable methods and assessments related to vegetation. The study also explains the vegetation production in different climate thermal changes and different vegetation adoption strategies. Wang *et al.* (2011) mention climate temperature influence to potential natural vegetation, distribution of vegetation and combined effects of extreme weather on vegetation. The study also divulges the concentration of CO_2 carbon dioxide absorption owing to the high temperature in Tibetan plateau China. The measurement climate changes, comparison of extreme weather in China, climate change impacts on natural vegetation types and uncertainties between climate change and its vegetation response in China are described by Futang and Zong-Ci (1995). Yao *et al.* (2011) explore climate changes owing to high mountains during Neogene which results in changes in paleogeography and also explored the influence of monsoon during Miocene in China, the intensity of Monsoon in Miocene, fossil floras in different locations of south China, presence of temperature and precipitation, warm and humid in ultimate influence on plant fossils. Yao *et al.* (2018) present Goji fruits, used for medicines and food in China. The cultivation of chine's fruits in different climatic areas gives different production and growth, also reveals the cultivation of different types of fruits in climatic regions and their uses for different purposes in China. Wang *et al.* (2018) assess climatic zones, dry fruits collection from different zones and the presence of mycotoxins in dry fruits. Ceccarelli *et al.* (2010) describe climate changes like increasing and decreasing temperature, CO_2 concentration and ice concentration. The study also reveals the influence of the breeding of plants in different climate changes, an adaptation of climate for the cultivation of plants. Li *et al.* (2019) classify variations in the growth of vegetation variations in the cultivation of vegetables owing to climate changes near the Yellow River basin, China. Propastin *et al.* (2008) explore climatic change, precipitation and the effect of precipitation on vegetation. The study also explores induced vegetation growth which may be less or higher in different duration on drylands and different influences of precipitation on human-induced vegetation. Zhongbao *et al.* (2008) expose climate change effects on vegetation, small and large variations in growth during four seasons of the Chinese Loess Plateau (1981–2006).

The study also reveals about developments for implementation of farmland for large vegetation construction which will be fruitful for ecology. Jingyun *et al.* (2004) study the current and past trend of variations in vegetation like increase temperature enhances

the vegetation and increase rainfall enhances the vegetation. He also studies the rise and fall of vegetation in coastal areas of China. Wang *et al.* (2010) discussed the influence of climate change on crop adaption for cultivation in China, suitability of farmers according to climate changes for cultivation like vegetables and some farmers like to cultivate wheat and maize and also explained seasonal changes and regional changes predict crop selection. Sun *et al.* (2011) specify Neogene climates and vegetation. High mountains during the Neogene result in huge changes in paleogeography. Yong *et al.* (2016) explain the significance of plant phenology for the indication of climate changes, growth season, decade season and lengthening of the growing season of various peach varieties from 1983 to 2012. The authors also explain the effects of winter chill and global warming on growth in China. The grain growth and cultivation during climate change in China affects the economy (Zhou and Turvey, 2014). The authors also describe the growth of grains of different crops in less and high precipitation. Sun *et al.* (1990) perceive climate changes with seasonal variations, precipitation in starting few days of opening flowers eggplant and also effects on fruit setting of eggplant. The study is useful for future cultivation and growth of eggplant.

Mo *et al.* (2009) expose the food crops like fruits, vegetables, water stress, increment or decrement of production in the North China Plain (NCP). The study also reveals developments of policies and systems to handle climate change for a better ecosystem in NCP. Enhancing dietary diversity, nutrition and health is addressed by Ebert (2017). Ebert also explained the effects of climate changes on vegetables like production, spreading insect pests and spreading diseases. The study explains developments and biological methods to create such types of vegetation breed which adjust in climate changes in the whole world to maintain the sustainability of food. Bisbis *et al.* (2018) analyze the physiology of vegetables, the productivity of vegetables and influence on production with the change of CO_2 concentrations, productivity influence by O_2 concentration and precipitation and temperature changes in Western Europe. The authors also explore the developments and technologies for secure and productive vegetable production; examine the importance of fruits and vegetables, good productivity and growth of different species of vegetables and fruits (Ming and Yun-wei, 1986); and also examine the growth of these fruits and vegetables helps to improve the environment and developments in cultivation and propagation techniques and methods. Grubben (1977) explains the significance of vegetables and seeds, temperature effects on vegetable growing, climate changes effects on seeds growth, cultivation of tropical vegetables, demand of high-quality seeds to bear climate changes and enhancement in yield.

Shi and Li (2010) discussed the different species of wing fruits and climate influence on fruit trees during the middle of the Miocene in China. He also discussed the importance of fruits in Fujian province and Southeast China. Wang *et al.* (2010) explain fossil plant and climatic effects during Palaeocene to Eocene, growth and productivity at high and low temperature in Fushun, China. Keatinge *et al.* (2011) scrutinize the importance of malnutrition, vitamins and minerals in vegetables, uncertainties in production of vegetable soybean. Burhan *et al.* (2017) articulate the worth of oilseed crops, reduction of oilseed crop yield owing to climate effects, the effect of climate on pollination and government developing strategies to overcome this problem. Zhao *et al.* (2007) study the climate effect on cultivation and weight of rice seeds. This study also reveals that climate change ultimately has effects on yields of grains in Pakistan and has effects on phonological phases of cotton during cultivation. The study also reveals an oasis is suitable for cotton seeds to enhance productivity and selection of dates for sowing seeds in an oasis of arid regions in northwest China (Huang and Ji, 2014). Zheng *et al.* (2016) explain the effects of

daytime temperature on soybean seeds, seeds filling in daytime temperature over the period 1987–2007. The study also reveals the enhancement of soybean yield during daytime temperature in Northeast China. Nawaz *et al.* (2019) describe the quality of kinnow fruit in different climatic regions, effects of abiotic and biotic stress, thermal effects on fruits in Vehari and Toba Take Singh like pests and fruit fly in May and June, better quality predictions in Sargodha which shows a difference in the quality of kinnow in different climatic regions. Shahid *et al.* (2016) discussed different genotypes of potatoes, effects of temperature on different genotypes of potatoes like high growth, less growth and moderate growth. The study explains the climate effect of microaerophilic and aerophilic conditions on potatoes. Akhtar *et al.* (2008) discussed the eminence of potato crops of different seasons in hilly areas of Pakistan. Gawronska *et al.* (1992) delineate about climatic conditions, effects of five potato clones cultivation on two different regions and effects of temperature on these clones; these clones having different yields in hotter and cooler areas. Khan *et al.* (2020) used deep learning models for fruit predictions. Iqbal *et al.* (2019) predict the bioenergy by using machine learning techniques. The growth estimation of education institutions by linear regression model is discussed by Iqbal and Luo (2019). Iqbal *et al.* (2018) discussed the relationship between heterogeneous transmission learning and other methods of machine learning. Ahmed *et al.* (2016) explore climatic conditions and their effects on fruit trees near roadsides show different productivity in the dusty climate in Miyyaghundi (Quetta) and Ghanjdori (Mastung), Pakistan. In Section 2, data source and econometric methodology are discussed, Section 3 deals with the result and methodology, and Section 4 will be some final remarks.

2. Data collection and econometric approach

2.1 Data collection

The findings of the data set were obtained from WDI (2018) related to total fruit production (total of five fruits, kg per hectare), fruit harvested area (hectares), total fruit yield (hectares), CO_2, rural population (million), agricultural labor force and energy consumption (kWh per capita).

2.2 Econometric approach

The aim of this study is to examine, using the autoregressive distributed lag-bound testing (ARDL) co-integrative approach, the links among energy use, carbon dioxide emissions, cropping areas and fruit crop production. The relationship between variables is stated as follows:

$$LogTFP_t = \delta_0 + \delta_1 LogFHA_t + \delta_2 LogTFY_t + \delta_3 LogCO2_t + \delta_4 LogRP_t + \delta_5 LogEC_t + \delta_6 LogALF_t + \varepsilon_t \quad (1)$$

As shown in equation (1), the effects of fruit harvested area, total fruit yield, carbon dioxide emissions, rural population, energy consumption and agricultural labor force on total fruit production crops. ε stand for the error terms and t represents the time.

2.3 Autoregressive distributed lag-bounds testing method

Pesaran (1997, 2000, 2001) and Pesaran and Shin (1998) presented ARDL's method to co-integration. Without the restricted vector error correction model, this method was applied to examine the long-term relation between energy consumption, changing weather conditions and fruit production. An economic analysis shows that the variables under consideration are long-lasting connected as expected by the model. The above definition means that the system has

long-run association features. The variation and means are constant in economic terms and do not depend on time. Though several observational tests have shown that variances and means are not compatible with time-series variables, many co-integration approaches are not used, understood or accurately measured to address this problem. For small sample data assets, the ARDL method is best calculated. To estimate as follows, the ARDL model is defined:

$$\begin{aligned}\Delta LnTFP_t = {} & \xi_0 + \xi_1 \sum_{i=1}^{j} \Delta LnTFP_{t-1} + \xi_2 \sum_{i=1}^{j} \Delta LnFHA_{t-1} + \xi_3 \sum_{i=1}^{j} \Delta LnTFY_{t-1} \\ & + \xi_4 \sum_{i=1}^{j} \Delta LnCO2_t + \xi_5 \sum_{i=1}^{j} \Delta LnRP_{t-1} + \xi_6 \sum_{i=1}^{j} \Delta LnEC_{t-1} \\ & + \xi_7 \sum_{i=1}^{j} \Delta LnALF_{t-1} + \delta_1 LogFHA_{t-1} + \delta_2 LogTFY_{t-1} + \delta_3 LogCO2_{t-1} \\ & + \delta_4 LogRP_{t-1} + \delta_5 LogEC_{t-1} + \delta_6 LogALF_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

Where δ refers to the operator of the differences and show the long-run coefficient. ε t stands for the error term. On the basis of the estimated F-statistics, the co-movement of the long run among the interest variables is calculated. Unlike other technologies, a pre-test for unit roots is not needed for the ARDL co-integration technologies. Consequently, when dealing with variables that are incorporated into separate orders, the ARDL co-integration method is preferable and the combination of both is robust if only one long-run relation is formed between the subordinates of the small sample size. The F-statistic (Wald test) is used to determine the long-run relationship of the underlying variables. Under this method, long-term relations in the series are determined when the F-statistics reach the critical value levels. The key advantage of this approach lies in its co-integration of the vector, where numerous co-integration vectors are present. If there is a long-term co-integration between CO_2, energy usage, cultivated region and labor force, the long-run relationship coefficients are calculated with the following equation and the output of fruit crops is found:

$$\begin{aligned}\Delta LnTFP_t = {} & \zeta_0 + \zeta_1 \sum_{i=1}^{j} \Delta LnTFP_{t-1} + \zeta_2 \sum_{i=1}^{j} \Delta LnFHA_{t-1} + \zeta_3 \sum_{i=1}^{j} \Delta LnTFY_{t-1} \\ & + \zeta_4 \sum_{i=1}^{j} \Delta LnCO2_t + \zeta_5 \sum_{i=1}^{j} \Delta LnRP_{t-1} + \zeta_6 \sum_{i=1}^{j} \Delta LnEC_{t-1} \\ & + \zeta_7 \sum_{i=1}^{j} \Delta LnALF_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

The error correction approach describes the speed changes that are required to restore the long-run equilibrium after a short-term shock. For the method that indicates changes in speed, shows the measured error correction coefficient term.

3. Results and discussion

3.1 Correlation, stationarity analysis and descriptive summary

The first concise data statistics used for estimating are provided in Table 1. All variables are normally distributed according to the Jarque–Bera test.

	LNFTP	LNALF	LNCO2	LNEC	LNFHA	LNFTY	LNRP
Mean	16.29	1.40	0.74	13.47	14.35	13.08	20.39
Median	16.13	1.42	0.76	14.05	14.72	12.83	20.44
Maximum	18.29	1.52	2.02	14.47	15.39	13.95	20.54
Minimum	13.72	1.18	−0.55	11.30	12.37	12.46	20.12
Std. dev.	1.45	0.10	0.77	1.13	0.97	0.47	0.133
Skewness	−0.08	−0.61	0.10	−1.00	−0.59	0.61	−0.66
Kurtosis	1.64	2.29	2.05	2.20	1.956	1.83	2.075
Jarque-Bera	4.48	4.91	2.25	11.30	6.09	6.86	6.39
Probability	0.10	0.085	0.32	0.003	0.047	0.032	0.04
Correlation analysis							
LNTFP	1						
LNALF	−0.95	1					
LNCO2	0.95	−0.96	1				
LNEC	0.84	−0.74	0.84	1			
LNFHA	0.96	−0.86	0.90	0.91	1		
LNTFY	0.92	−0.95	0.92	0.67	0.79	1	
LNRP	0.15	0.10	0.05	0.49	0.38	−♠0.17	1

Table 1.
Correlation matrix and descriptive statistics

However, the approximate results of Table 1 correlation analysis indicate that carbon emissions, energy consumption, fruit harvested area, total fruit yield and agriculture labor force are related significantly and positively to the production of fruit crops. The authors verified whether the certain variables were stationary at the level/first difference. Augmented Dickey-Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were used to check that variables are stationary or not. The result of these above tests is shown in Table 2.

3.2 Autoregressive distributed lag-bound testing

Apply the ARDL limit test to illustrate how long-term co-integration occurs. The present research presents the long-run co-integration results of ARDL, shown in Table 3, and demonstrates the existence of long-run co-integration relationships between total fruit production, fruit harvested area, total fruit yield, CO_2, energy consumption and agriculture labor force in China. Several diagnostic tests were applied to check the stability of the ARDL approach and inspected. The F-statistics, R^2 and adjusted R^2 were valid as shown in Table 3. The test results of co-integration are shown in Table 4 which explained that the independent variables (fruit harvested area, total fruit yield, CO_2, agriculture labor force, energy consumption) and the dependent variable (total fruit production) also showed long-term co-integration linkages.

3.3 Long-run coefficients and short-run dynamics

The long- and short-run coefficients estimates of the ARDL model are shown in Table 5. According to long-term coefficients, fruit production is negatively affected by rural population and CO_2, which means an increase in CO_2 emissions of 1% and rural population will, respectively, decrease the production of fruit crop by −0.59% and −1.97%. Also, this research has found in the long run that energy consumption, harvested area and agriculture labor forces have a significant and positive impact on production of fruit crop.

These results can be interpreted as an increase of 1% in an energy consumption, harvested area, total fruit yield and agriculture labor force to 0.17, 1.52, 1.80 and 4.33, respectively, increase in fruit crop production. The short-term emission coefficient of CO_2 is negatively related to the production of fruit crops in China. In addition, the analysis finds the

Table 2.
Result of unit root test

		ADF test statistic		PP test statistic		KPSS test statistic	
Variables	Tests	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
LNFTP	Level	−1.7353	−0.9081	−1.642	−0.9713	0.9335	0.1143
	Ist diff	−4.4113	−4.6188	−6.9031	−7.2934	0.2978	0.0973
LNALF	Level	3.5953	−0.2425	3.6792	−0.2508	0.9066	0.229
	Ist diff	−3.4034	−8.4779	−7.0534	−8.4096	0.611	0.0645
LNCO2	Level	−0.6564	−3.5274	0.2897	−4.836	0.8898	0.0891
	Ist diff	−5.7118	−5.4895	−6.4558	−6.0459	0.2227	0.1071
LNEC	Level	−1.758	−1.4063	−1.7677	−1.3918	0.7466	0.2003
	Ist diff	−7.5657	−7.7181	−7.5657	−7.7338	0.2373	0.0649
LNFHA	Level	0.1749	−0.8955	−2.5209	−0.6262	0.88	0.2516
	Ist diff	−5.4102	−5.9704	−5.3995	−5.9938	0.5301	0.0516
LNFTY	Level	0.382	−1.8534	0.7396	−1.6874	0.8446	0.2076
	Ist diff	−8.9334	−9.076	−8.9334	−9.2609	0.3204	0.08
LNRP	Level	−2.1066	−2.6098	−1.4212	0.3019	0.2509	0.2407
	Ist diff	−0.1775	−2.6137	−0.3097	−5.5931	0.8423	0.0581

use of energy in fruit crops had a positive and significant effect. In addition, the analysis finds the use of energy in fruit crops had a positive and significant effect. The coefficient for the energy use in short run was 0.96 ($P < 0.04$), which means that a 1% increase in energy consumption would lead to an increase in the production of fruit crops of 0.96%. The coefficient of harvesting for the harvested area was statistically significant, and this means that a 1% increase would result in a 0.57% increase in the production of fruit crops. The study also investigated the presence of long-term co-integration with Johansen and Juselius.

Significance	*I*(0)	*I*(1)
Critical values bounds		
10%	1.99	2.9
5%	2.27	3.3
2.50%	2.55	3.6
1%	2.88	3.9
Diagnostic test		
R-squared	0.999240	
Adjusted R-squared	0.998321	
F-statistic	6.008453	
Prob (F-statistic)	0.000000	

Table 3.
Results of ARDL-bounds test

Hypothesized no. of CE(s)	Trace statistic	0.05 critical value	Prob.**
None *	153.4053	125.6154	0.0003
At most 1	90.57058	95.75366	0.1078
At most 2	52.86522	69.81889	0.5111
At most 3	32.30343	47.85613	0.5954
At most 4	15.06970	29.79707	0.7756
At most 5	4.770919	15.49471	0.8327
At most 6	0.007651	3.841466	0.9298
Maximum Eigenvalue			
None *	62.83469	46.23142	0.0004
At most 1	37.70536	40.07757	0.0904
At most 2	20.5618	33.87687	0.7166
At most 3	17.23372	27.58434	0.5599
At most 4	10.29879	21.13162	0.7162
At most 5	4.763268	14.2646	0.7714
At most 6	0.007651	3.841465	0.9298

Table 4.
Johansen co-integration tests

Variable	Coefficient	SE	*t*-statistic	Prob.
Estimated long-run coefficients				
LNALF	4.334018	2.291247	1.891554	0.0731
LNCO2	−0.593629	0.240443	2.468897	0.0227
LNEC	0.173955	0.104210	1.669278	0.1106
LNFHA	1.528510	0.173933	8.787913	0.0000
LNFTY	1.807375	0.251749	7.179264	0.0000
LNRP	−1.977667	0.917989	2.154346	0.0436
C	3.111270	13.91651	0.223567	0.8254

Table 5.
Estimated long- and short-run coefficients as of error correction model

The agriculture labor force has also a positive effect on the production of fruit crops which means labor force would lead to a 0.75% increase in fruit crop production.

3.4 Diagnostic tests

Our analysis then carried out several diagnostic tests as shown in Table 6 following an investigation into the long- and short-term coefficients of the ARDL model. Diagnostic test results such as the Breusch–Godfrey Serial Correlation LM and autoregressive conditional heteroskedasticity tests reveal that there are no autocorrelation problems with the ARDL approach. Similarly, the Ramsey RESET and Jarque – Bera tests demonstrated that the form of the ARDL functional model is correct with no misspecifications and that the residuals were normally distributed. Testing was performed using CUSUM and CUSUMSQ for the constancy of the ARDL model. The plots of CUSUM and CUSUMSQ had a 5% significance as shown in Figures 1 and 2, so the ARDL approach over the period is constant.

3.5 Results of Granger causality test

This analysis has used Granger's pairwise causality test to examine the causal direction of the variables; the causal links were analyzed between an FHA (natural logarithm fruit harvested area), lnTFY (natural logarithm total fruit yield), ln CO2 (natural logarithm carbon dioxide emission), lnRP (natural logarithm rural population), lnEC (natural logarithm energy consumption), lnALF (natural logarithm agricultural labor force) and lnTFP (natural logarithm total fruit production). Results of the pairwise Granger causality technique are summarized in Table 7. The null hypothesis of carbon dioxide emissions does not lead to decline in production of fruit crops which is rejected at the 1% level. It has been shown that lnCO2 and lnTFP are bidirectional sources. The null hypothesis of energy consumption does not increase the quality of fruit crops which is also rejected at 5%.

The unidirectional causality of lnEC and lnTFP is demonstrated. Therefore, the zero assumption that the cultivated area does not cause increases in fruit crop is rejected at a significant level of 10%. It is shown that the lnTHA and lnTFP affect bidirectionally.

Table 6.
Diagnostic tests of the ARDL model

Diagnostic tests	F-statistic	Probability
Breusch Godfrey serial correlation LM test	0.890995	0.4276
Heteroscedasticity #est: ARCH	0.522888	0.4729
Normality test	3.603798	0.8544

Figure 1.
Cumulative sum of recursive residuals (CUSUM)

4. Forecasting of climate impact on fruit using machine learning

There are several technologies available to forecast data such as linear regression, support vector machine, Naive Bayesian classifier and so on. Different methods have several analyzing procedures. Some of the predicting techniques are discussed below.

4.1 Logistic regression

In several applications, logistic regression was used for future forecast. Logistic regression needs to generate method coefficients to forecast a logit transformation of the probability of an attribute of interest being present.

4.2 Results of the Granger causality test

This analysis has used Granger's pairwise causality test to examine the causal direction of the variables; the causal links were analyzed between an FHA, lnTFY, lnCO2, lnRP, lnEC, lnALF and lnTFP. Results of the pairwise Granger causality technique are summarized in Table 7.

The null hypothesis of carbon dioxide emissions do not lead to decline in production of fruit crops is rejected at the 1% level. It has been shown that lnCO2 and lnTFP are bidirectional sources. The null hypothesis of energy consumption does not increase the quality of fruit crops is also rejected at 5%. The unidirectional causality of lnEC and lnTFP is demonstrated. Therefore, the zero hypothesis that the cultivated area does not cause increases in fruit crops is rejected at a significant level of 10%. It is shown that the lnTHA and lnTFP affects bidirectionally.

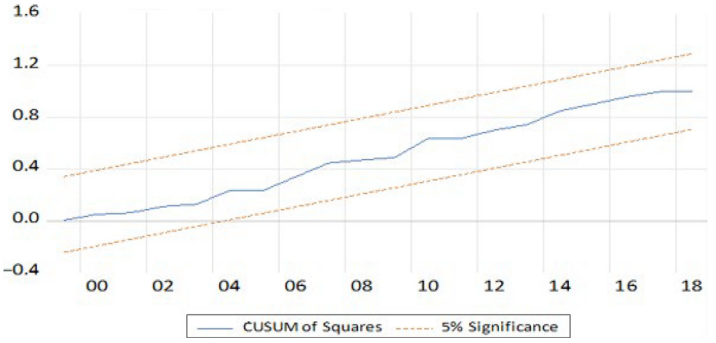

Figure 2.
Cumulative sum of squares of recursive residuals (CUSUMSQ)

Null hypothesis	F-statistic	Prob.
LNALF does not Granger cause LNTFP	0.15581	0.8561
LNTFP does not Granger cause LNALF	0.07386	0.9289
LNCO2 does not Granger cause LNTFP	0.10046	0.9046
LNTFP does not Granger cause LNCO2	3.75293	0.0302
LNEC does not Granger cause LNTFP	0.47713	0.6233
LNTFP does not Granger cause LNEC	0.26653	0.7671
LNFHA does not Granger cause LNTFP	1.06777	0.3513
LNTFP does not Granger cause LNFHA	2.0007	0.1457
LNTFY does not Granger cause LNTFP	0.39536	0.6755
LNTFP does not Granger cause LNTFY	1.99138	0.147
LNRP does not Granger cause LNTFP	1.09767	0.3414
LNTFP does not Granger cause LNRP	18.9107	7.0007

Table 7.
Pairwise Granger causality test results

The logistic regression distribution contains the estimated probabilities to lie between 0 and 1. The linear equation will use the first and then sigmoid function for the result and obtain a value of 0 to 1.

$$SF = \frac{1}{1 + e^{-z}} \tag{4}$$

The above Sigmoid method is used for logit. To compute inaccuracy and cost function, the cost function of linear regression is mentioned as follows:

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{j=1}^{m} \left(k_\theta(z^j)\right) - t^j)^2 \tag{5}$$

The logistic regression cost function is as follows:

$$= -\frac{1}{m} \left[\sum_{j=1}^{m} t^j \log k_\theta(z^j) + (1 - t^j) \log\left(1 - k_\theta(z^j)\right) \right] \tag{6}$$

Note: *t* always 0 *or* 1.

4.3. K-nearest neighbors classifier

Both classification and regression problems may be solved with K-nearest neighbor (KNN) classifiers. KNN is among the most significant fundamental yet important artificial intelligence classification algorithms. KNN belongs to the field of education and is usually used for detecting patterns, data gathering and intrusions.

4.4 Decision tree classifier

Classification tree supports the classification, regression and also used in supervised learning. The decision tree (DT) has been one of the statistical modeling techniques being used in data mining, analytics and neural network.

DT are designed using an algorithmic method that finds ways of splitting a collection of data depending on distinct conditions. DT algorithm is a non-parametrically supervised learning process, used for regression and classification. In data mining DT may also be described as a combination of mathematical and computational techniques that help in the categorization, description, and generalization of a given collection of data. Data presented in the form of records such as:

$$(z, T) = \left(z_1, z_2, z_3, z_4, \ldots . z_n T\right) \tag{7}$$

Here, the dependent variable Z is the target variable that we are trying to classify or generalize. Z1, Z1, Z3, Z4. . ..Zn is a feature of vector Z.

4.5 Random forest classifier

Random forests are an ensemble learning algorithm to classify, regressive and perform specific tasks. The random forest training algorithm uses the common methods of bootstrap for tree learners. With a training set A = a1,. . .,am, with responses B = b1,. . .,bm, repeated bagging (K times), randomly selects the sample and substitutes a training set for trees.

For k = 1... K, sample, by substituting m examples from A, B, call these Ak, Bk. Tree can be trained by a regression tree or classification tree on Ak, Bk. Prediction and training may be made for unseen samples concerning using averaging the forecasts for all regression trees and for the most voting classification trees.

$$\hat{f} = \frac{1}{K}\sum_{k=1}^{K} f_k(a') \tag{8}$$

This bootstrapping procedure improves model performance as the model variance is reduced without increasing the bias. It implies that while single tree forecasts are highly noise-sensitive, the usual number of trees does not occur unless the trees are connected. Train many trees in the same workouts simply gives trees strongly associated or often the similar tree, if there is a probabilistic training algorithm; test set bootstrap is a method for the trees to be de-correlating by presenting various sets of training. Furthermore, a standard deviation between the forecasts of all individual regression trees a' can be assessed for predictive uncertainty.

$$\psi = \sqrt{\frac{\sum_{k-1}^{K}\left(f_k(a') - \hat{f}\right)^2}{K-1}} \tag{9}$$

K is an unrestricted parameter of the number of samples. Typical use depends on training set of nature and size, by used several thousand trees. Some trees K is found by noting the "out of bag" error or by cross-validation, signify forecast error on ai every sample, only use ai trees in their bootstrap sample sets. After several trees have been fit, the error in training and testing tends to escape.

4.6 Total fruit production

There is a list of fruits that are grown in China. From China inside and outside, common fruits are used in this paper like apples, bananas, citrus, grapes and pears. China is fortunate in that it has a great deal of soil variety as well as a different range of ecological and climatic circumstances, which reach from warm to temperate, with very cold winters. This allows the country to raise many kinds of plants, shrubs, trees, creepers and vines, which produce a large variety of vegetables and fruits. Total fruit production (apples, bananas, citrus, grapes, pears) of China in 1961 was 910,547 tons and in 1970 fruit production succeeded 159,330 tons. The study in 2000, production improved and succeeded 677,748 tons. In 2010, 2015 production increased and reached 764,384, 820,948 tons, respectively. Fruit production is shown below in Figure 3 from 1960 to 2018.

The overall energy used last year in 2018 amounted to 4.64 billion tons. Chinese energy consumption in 2003 amounted to an equivalent of 1,678 million tons (MtCE) of coal, this makes it the world's second biggest market after the USA. Today, China's position on the global energy market is projected to continue at a development rate of 7%–8% over the decades (Crompton and Wu, 2005).

According to the World Bank's development indicators collection, the rural population (percent of the total population) in China was 40.85% in 2018. As the nation with the second-highest CO_2 gas emitter, China saw a dramatic decrease in CO_2 emissions between 1991 and 2000, but ever after that, the rate of decrease has slowed and the level of CO_2 emissions increased in 2003. In China, amount of CO_2 in 1961 was 1.17038% EN.ATM.CO2E.PC, it decreased in 1971 to 0.942934%. From 1972 it again increased and reached 2.038410 in 1988.

Again increase and in 2003 it reached 3.007083%. In 2012, it reached 7.241515% and now onward it slowly increased and in 2018 it reached 7.185809% as shown in Figure 4. CO_2 is produced by different sectors (World Bank, 2016) as shown in Figure 5. According to World Bank indicator, in 2018 China participation rate of labor was 45.44%. In this paper, the authors consider only agriculture labor force. In 1961, agriculture labor force was 99.40000% and in 1980 it decreased and reached to 80.009998%. In 1990, it again decreased to 62.762939% and in 2010 it reached to 36.700000%. As seen in Figure 6, it reached 26.101999% in 2018.

The difference between harvest and yield is: yield is the quantity of a harvest. The yield is what is produced. Farmland will yield fruit and grain. The harvest is the act of gathering it. Once the crops are ready, they will be harvested. In 1961, total harvested area was 237,822 ha and fruit total yield 291,833 hg/ha. In 1980, both were increased and reached 1,112,489 ha and

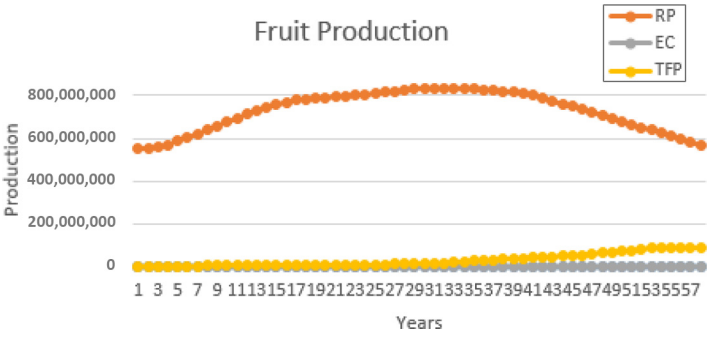

Figure 3.
Total fruit production, energy consumption and rural population

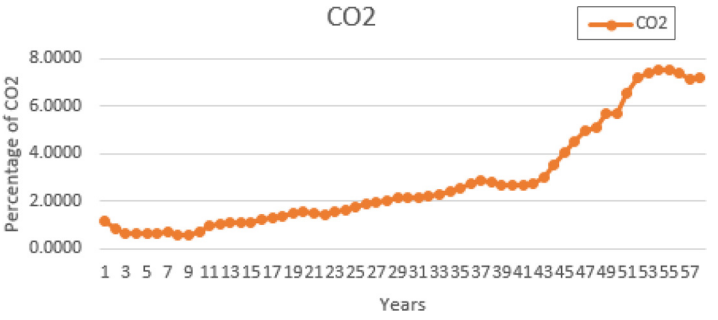

Figure 4.
Carbon dioxide emission

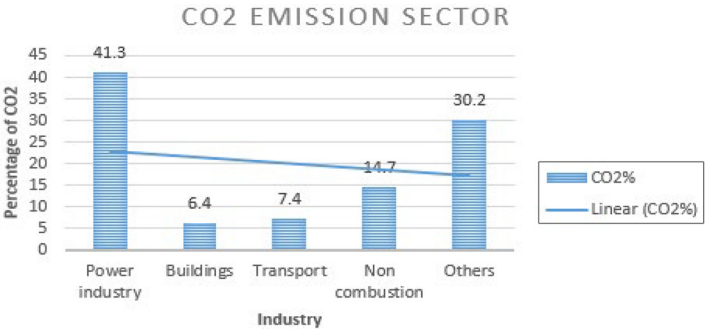

Figure 5.
Sector wise consumption of carbon dioxide emission

358,185 hg/ha, respectively. In 2000, it reached to 3,882,747 ha and 612,109 hg/ha. In 2018, it increased and reached 4,374,381 ha and 1,152,266 hg/ha as shown in Figure 7.

The authors used four distinct algorithms to forecast and find good precision in potential climate impacts on fruit production. Table 8 shows the accuracy of the classification of three baseline climate influence approaches for fruit in China. The findings reveal that KNN does

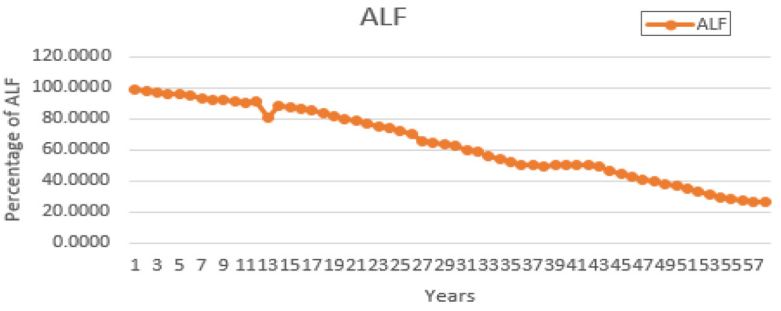

Figure 6.
Agriculture labor force

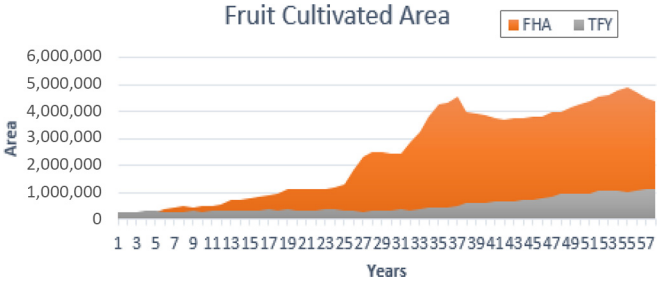

Figure 7.
Fruit cultivated area

Methods	Data set	Predicted data	Accuracy
LR	Fruit data of China 1961–2018	1961–2035	90.00 ± 2%
KNN	Fruit data of China 1961–2018	1961–2035	85.00 ± 2%
DT	Fruit data of China 1961–2018	1961–2035	70.00 ± 2%
RF	Fruit data of China 1961–2018	1961–2035	75.00 ± 2%

Table 8.
Predicted results (accuracy)

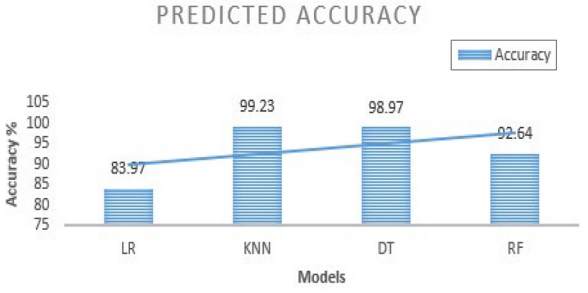

Figure 8.
Graph of predicted accuracy

much better than the three other baseline approaches. The overall accuracy of LR classification for data sets is 99.23%. In addition, the authors see that the effects of 15 repetitive cycles on average (shown in Table 8 and Figure 8) are minor variations compared with the increases in precision, which suggests that LR is performed accordingly with the random initialization.

5. Conclusion

In this study, an effort was through to assess the long-term impacts of Chinese production on five fruit cultivations by construing the annual indicators from 1961 through 2018. The analysis used the ARDL model and the Johansen co-integration test to assess long-run linkage among fruit production and energy consumption, carbon dioxide emissions, harvested or yield region, agriculture labor force. The current research used PP, KPSS and ADF root tests before testing of ARDL-bound co-integration method. The long-run presence of statistically significant co-integrating factors is correlated and has been confirmed by the co-integration approach results for ARDL-bounds. The results of long-run CO_2 emission and rural coefficients have adverse effects on the production of fruit crops. The energy consumption, agricultural labor force, fruit harvested area and total fruit yield have optimistic impacts on tropical fruit production. These findings indicate that CO_2 emissions have increased by 1%, and the rural population will decrease fruit crop production by −0.59% and −1.97% in the long run. These results also explain that a 1% increase in the agricultural labor force, energy consumption, fruit harvested area and total fruit yield will gain fruit crop production in 0.17%, 4.33%, 1.52% and 1.80%, respectively, in the long run. Based on the study results, to provide the country with food protection to resolve the adverse climate change impact, temperature stress and immune species, fruit seedlings should be produced and implemented. Following concepts may be applied for future work; it is possible to incorporate various deep learning algorithms and have good guidance for the creation of a new model. It is also possible to equate the growing population ratio with fruit production and compare fruit production and policies in developed and underdeveloped countries. Besides, the government needs to pay attention to improve agricultural sector infrastructure.

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