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The impacts of climate change and smallholder farmers’ adaptive capacities on rice production in Chengdu, China: macro-micro analysis

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Abstract

Among other cultivated crops, rice is the most sensitive to climate variability over its growing season. As such, over-reliance on climate conditions for rice farming calls for a wide range of strategies critical to curtailing the adverse impact of climate change on rice production. Notwithstanding, there remain considerable gaps in our knowledge of adaptive capacities among China’s small-scale farmers who depend on climate conditions for farming. This study is broadly divided into two parts that are distinct but connected. First, we assess the effects of climate change on rice production in Chengdu (China), covering the period 2000Q1-2016Q4. We show that mean rainfall and temperature induce rice production positively in the long and short run. While temperature variability insignificantly impacts rice production in the long run, it plays a substantial role in the short run. Rainfall variability and the interaction term between temperature and precipitation are unfavourable to rice production in the long and short run. The results reveal that energy usage and fertilizer application support rice production, although the impact of energy consumption is significant in the short run. Second, we used a survey of 383 smallholder rice growers in Chengdu to examine farmers’ adaptive capabilities to climate change in rice production. The results show that farmers’ adaptive capabilities significantly affect rice production. We argue that the centrepiece of improving rice production under continuous climate change is for farmers to develop a high adaptive capacity to the changing climatic conditions. This is achieved through intensive education on available adaptation strategies and their long-term implications.

1. Introduction

Demand for food is rising globally. At the same time, worldwide agriculture systems face several challenges threatening crop production. Many scholars share deep concerns about the adverse effects of commodity price volatility, competition for agricultural land, and inadequate financial supply on food production (Zhang and Liu 2020; Supriya and Mamilla 2022). Notwithstanding, climate shocks reinforce the adverse impact of non-climate stressors on farming (Hasan et al. 2016; Dubey and Sharma 2018). Climate change affects agriculture in several ways. First, episodes of high floods, droughts, extreme heatwaves, and tropical cyclones decrease crop production (Marvin et al. 2013; Thornton et al. 2014; Myers et al. 2017; Pathak et al. 2018; Rahman and Rahman 2019). The Intergovernmental Panel on Climate Change (2007) report, for example, indicates the possibility of a 10 to 40% loss in crop production in India by 2100 due to climate change. Continuous climate change is also affecting China’s agriculture (Qin 2015), thus exerting severe stress on the country’s food security (Huang et al. 2017; Zhou et al. 2017). Second, the purported consequences of climate change are quite severe for
small-scale agriculture. Small-scale farmers rely extensively on environmental factors, and they typically lack access to institutional support, financing facilities, and technological equipment needed to cope with climate shocks (Morton 2007; Altieri and Koohafkan 2008; Collier and Dercon 2009; Jayne et al. 2010; Pettengell 2010; Vorley et al. 2012; Harvey et al. 2014). Besides, rain-fed agriculture characterizes small-scale farming, and farmers in developing regions in Asia, Africa, Latin America, and the Caribbean are often susceptible to the effects of climate change variability (Frank and Buckley 2012; Harvey et al. 2014; Holland et al. 2017; Harvey et al. 2018).

In this study, we present a comprehensive micro-macro analysis of the impact of climate change on rice producers in China. Since the 1970s, China has become one of the world’s largest rice-growing regions (State Environmental Protection Administration 2003; United States of Agricultural Department 2017). China accounts for about a quarter of the world’s rice cultivated area and over a third of the global rice production (State Environmental Protection Administration 2003; United States of Agricultural Department 2017).

Although rice accounts for over 35% of China’s grain production, it only occupies 31% of the country’s total planting area (National Bureau of Statistics of China 2018). Rice is the staple food for more than 65% of the populace (Zhang et al. 2005), and it remains the subsistence crop for most smallholder farmers and consumers in rural China (Peng et al. 2009). As the country’s population grows, China requires an approximately 20% increase in rice production by 2030 to meet demand if per capita rice consumption is maintained at the current level (Cai and Chen 2000). Yet, the challenges of achieving food self-sufficiency are many, given the country’s socio-economic and physical environment (Peng et al. 2009).

Among other crops cultivated in China, rice is one of the most vulnerable to climate extremes (Roy 2009). The total rice production in China is projected to decline by 15.62% to 24.26% and 25.95% to 45.09% in 2030 and 2050, respectively, if extreme drought and flood worsen (Xin et al. 2013). Existing evidence shows that if the climate gets hotter, it could destroy crop production systems (Deryng et al. 2014). When climate change patterns get more unpredictable, with the associated floods and droughts variabilities, its effect on crop production and food security would be detrimental (Lesk et al. 2016).

Despite the impact of climate change on rice production, scholars are optimistic about the role of farmers’ adaptation strategies in mitigating the overall impact of climate change on small-scale farming (Pickson and He 2021). Farmers have various options available to deal with the effects of climate change. Different adaptation strategies can improve soil quality and increase its resilience. These include planting trees, establishing a proper irrigation system, and applying fertilizers timely (Bradshaw et al. 2004; Howden et al. 2007; Morton 2007; Nhemachena and Hassan 2007; Kurukulasuriya and Mendelsohn 2008; Bryan et al. 2009; Deressa et al. 2009; Molua 2009). Developing effective adaptation strategies is critical to minimizing the harmful effects of climate change (Tesfaye, Seifu 2016). It is argued that without adaptation, the vulnerability of smallholder farming households will worsen, especially if climate change becomes unpredictable (Smit and Pilifosova 2001). Notwithstanding, evidence shows that the efficacy of climate change adaptation depends on the capacity of a system, region, or society in which such strategies are implemented (Morton 2007). This is because the varying capacities, sensitivity, and exposures of different socio-economic groups and institutions can affect the adaptation efforts (Intergovernmental Panel on Climate Change 2007).

Several empirical studies on the effects of climate change on cereal production have been carried out in China (Xiong et al. 2014; Liu et al. 2017; Zhou et al. 2017; Lv et al. 2018; Chen and Pang 2020; Liu et al. 2020; Pickson et al. 2020; Tian et al. 2020; 2020; Jiang et al. 2021; Pickson et al. 2021; Wu et al. 2021; Zhang et al. 2021; Pickson et al. 2022). However, empirical evidence on the impacts of climate change and smallholder farmers’ adaptive capacities on rice production in Chengdu, China, remains scanty. A recent study by Pickson and He (2021) concentrated on climate perceptions, adaptation constraints, and determinants of adaptive capacity to climate change among small-scale rice growers in the study area. The study, however, ignored the effects of smallholder farmers’ adaptive capacities to climate change adaptation on rice cultivation. As part of our contribution, we argue that some farmers have a higher level of resilience to climate change than others due to their specific characteristics (Mabe et al. 2012). Hence, classifying the smallholder farmers’ adaptive capacities to climate change into two categories—high and low adaptive capacities to adaptation strategies—permits a compelling examination of their impacts on rice production.

Not only did we assess the impacts of farmers’ adaptive capacities to climate change on rice output, but the long-run and short-run effects of climate change on rice production in Chengdu are also critically discussed. Our paper also differs from the study by He et al. (2022), which used cereal production to measure agricultural output in China’s Sichuan Province. We note that, by considering cereal production in its aggregated form, the authors limit differing characteristics such as crop type, which does not enhance our understanding of the responsiveness of a specific crop to climate change extremes. To reduce such biases, we focus on rice production and thus provide specific and suitable policy recommendations to address the susceptibility of rice production to climate change. Our study contributes a different argumentative trajectory to the existing literature on climate change by addressing the following questions: (i) What are the impacts of climate change on rice production in
Chengdu? (ii) What are the effects of smallholder farmers’ adaptive capacities to climate change adaptation strategies on rice output in Chengdu?

2. Econometric methodology

2.1. Data characteristics
In this study, we employed both primary and secondary data. Specifically, at the initial stage, we utilized quarterly data covering 2000Q1-2016Q4 to assess the role of climate change in rice production in Chengdu (China). The data on fertilizer usage, mean temperature, energy consumption, mean rainfall, and rice production were extracted from the Chengdu Bureau of Statistics (2018) and China’s National Bureau of Statistics (2018). We used the coefficient of variation (CV) to determine rainfall and temperature variabilities in Chengdu over the considered period. Except for the climatic variables, we transformed the other variables into natural logarithms. This follows the argument that untransformed climatic data gauge the direct effects of the climatic variables on agricultural production (see Kariuki 2016; Pickson et al 2020).

Additionally, 383 smallholder rice farming households on the fringes of Chengdu (i.e., Dayi, Xinjin, Qionglai, and Pidu, as shown in figure 1) were used for the micro-level analysis. These small-scale rice growers depend extensively on climate factors for farming. Moreover, a survey to elicit primary data on several adaptation strategies adopted by smallholder farmers amid climate change impacts on the fringes of Chengdu (specifically, Dayi, Xinjin, Qionglai, and Pidu) was conducted from March to April 2019. Figure 1 shows the map of the study area—Chengdu (China).

2.2. Model specifications
2.2.1. The impacts of climate change on rice production
This section presents the model specification examining the effects of climate change in Chengdu (China). Following Pickson et al (2020), Pickson et al (2021), and Pickson et al (2022), we specify the following rice production model that accounts for the impact of climate change:

\[ RCP = f (ECON, \ FERT, \ TEMP, \ TEV, \ RAIN, \ RAV, \ TEMP \times RAIN) \]  

Where \( RCP \) stands for rice production, \( ECON \) represents energy consumption, \( FERT \) signifies the consumption of chemical fertilizers, \( TEMP \) is the average temperature, \( TEV \) connotes the temperature variability, \( RAIN \) denotes average rainfall, \( RAV \) is rainfall variability. Also, \( TEMP \times RAIN \) represents the interaction between temperature and precipitation.

Equation (1) is expressed in a regression model as follows:

\[ RCP_i = \lambda_0 + \lambda_1 ECON_i + \lambda_2 FERT_i + \lambda_3 TEMP_i + \lambda_4 TEV_i + \lambda_5 RAIN_i + \lambda_6 RAV_i + \lambda_7 (TEMP \times RAIN)_i + \mu_i \]  

Where \( \lambda_0 \) represents a constant term. The notation \( \lambda_i \) (for \( i = 1, 2, 3, \ldots, 7 \)) represents the coefficients of the left-hand side variables to be estimated. Also, the notation \( \mu_i \) is the idiosyncratic error term, which is assumed to
be identically and independently distributed. Table 1 depicts the description of the variables featured in the rice production model in equation (2).

2.2.2. The impacts of adaptive capacities to climate change adaptation on rice output

Empirically, crop output is defined as a function of labour, capital, land, and agro-climatic factors as in the studies of Chen et al. (2004), Mundlak (2001), Herath and Kawasaki (2011), Blanc (2011), Acquah and Kyei (2012), Mabe et al. (2012), Mahmood et al. (2012), and Kumar and Sharma (2014). We specify an extended model that permits rice input-output analysis to effectively assess the impact of adaptive capacities to climate change on rice output. The empirical model for rice output is expressed as:

\[ QR_i = \lambda_0 + \psi_1 X_i + \psi_2 C_i \]  (3)

Where \( QR \) connotes total rice output for the \( i \)th farmer; \( \lambda_0 \) is the intercept, \( \psi_1 \) represents the unknown parameters of the regressors, \( X_i \) indicates a vector of control variables such as the age (AGE) and educational level (EDU) of farming household head, household size (HHS), monthly household income (INCO), access to agricultural extension services (AEXT), participation in a farmer-based organization (FBO), farm labour (LAB), and capital stock (CAP). \( C_i \) represents a vector of agro-climatic variables like temperature, rainfall, and relative humidity. The axiom here is that the degree of a farmer’s adaptive capacity to climate change adaptations influences crop output supposing that all other factors are constant. In this study, the adaptive capabilities are, therefore, classified as farmers with low adaptive capacity (LAC) and farmers with high adaptive capacity (HAC) to capture their respective impacts on rice output (see Mabe et al. 2012; Eyasmin et al. 2017). Table 2 presents the description of the explained and explanatory variables specified in equation (3).

2.3. Estimation strategies

2.3.1. Stationarity tests

The underlying characteristics of the time-series data cannot be assumed stationary. Several pre-estimation checks were conducted to avoid estimating spurious or misleading regression outcomes. In particular, the Ng-Perron unit test was utilized to examine the stationarity properties of the concerned variables. The Ng-Perron (2001) provided four (4) test statistics that are based on Phillips (1987), Bhargava (1986), Phillips and Perron (1988), and Elliot et al. (1996). These four tests of Ng and Perron (2001) are \( MZ_{ts}, MZ_t, MSB, \) and \( MP \). The \( MZ_t \) and \( MZ_s \) are the modified forms of \( Z_t \) and \( Z_s \) tests developed by Phillips (1987) and Phillips & Perron (1988). The MSB was obtained by modifying the \( R \) test of Bhargava (1986), and finally the \( MP \) is derived from
the Point Optimal test of Elliot et al (1996). The modified statistics of the Ng-Perron (2001) unit root test are as follows:

\[ MZ^d_{\alpha} = \frac{T^{-1}(y^d_{\alpha})^2 - f_0}{2k} \]  

(4)

for \( k = \sum_{i=2}^{y} (y^d_{i-1})^2 / T^2 \) and \( f_0 \) connotes the frequency zero spectrum estimation

\[ MZ^d = MZ^d_{\alpha} \times MSB \]  

(5)

\[ MSB^d = \left( \frac{k}{f_0} \right)^{1/2} \]  

(6)

\[ MP^d_i = \begin{cases} \varepsilon^2 K - \varepsilon T^{-1}(y^d_{\alpha}) / f_0, & \text{if } x_i = (1) \\ \varepsilon^2 K + (1 + \varepsilon) T^{-1}(y^d_{\alpha})^2 / f_0, & \text{if } x_i = (1, t) \end{cases} \]  

(7)

for \( \varepsilon = \begin{cases} -7ifx_i = (1) \\ -13.5, & \text{if } x_i = (1, t) \end{cases} \)

2.3.2. ARDL cointegration test

As part of the estimation strategy, the autoregressive distributed lag (ARDL) technique developed by Pesaran et al (2001) was considered to examine the dynamics of climate change and rice production. The ARDL framework enables us to investigate possible long-run equilibrium relationships between rice production and its explanatory variables as specified in equation (1). The ARDL technique has several advantages. Unlike conventional cointegration approaches (Engle and Granger 1987; Johansen and Juselius 1990), the ARDL technique produces reasonable estimates even when the variables are either \( I(1), I(0), \) or are mutually integrated \( I(0) \) and \( I(1) \). It is also suitable for small sample sizes, and the results for long-run and short-run parameters are concurrently estimated. Generally, the ARDL bounds testing to cointegration approach is as follows:

\[ \Delta \ln RCP_i = \beta_0 + \sum_{i=1}^{p} \delta_{i1} \Delta \ln RCP_{i-i} + \sum_{i=1}^{q} \delta_{i2} \Delta \ln \text{ECON}_{i-i} \]

\[ + \sum_{i=1}^{q} \delta_{i3} \Delta \ln \text{FERT}_{i-i} + \sum_{i=1}^{q} \delta_{i4} \Delta \text{TEMP}_{i-i} \]

\[ + \sum_{i=1}^{q} \delta_{i5} \Delta \text{TEV}_{i-i} + \sum_{i=1}^{q} \delta_{i6} \Delta \text{RAIN}_{i-i} + \sum_{i=1}^{q} \delta_{i7} \Delta \text{RAT}_{i-i} \]

\[ + \sum_{i=1}^{q} \delta_{i8} \Delta (\text{TEMP} \ast \text{RAIN})_{i-i} + \lambda_1 \Delta \ln \text{RCP}_{i-i} \]

\[ + \lambda_2 \Delta \ln \text{ECON}_{i-i} + \lambda_3 \Delta \ln \text{FERT}_{i-i} + \lambda_4 \Delta \text{TEMP}_{i-i} \]

\[ + \lambda_5 \Delta \text{TEV}_{i-i} + \lambda_6 \Delta \text{RAIN}_{i-i} + \lambda_7 \Delta \text{RAV}_{i-i} \]

\[ + \lambda_8 (\text{TEMP} \ast \text{RAIN})_{i-i} + \mu_i \]  

(8)

For \( \Delta \) is the first-difference operator, and the null hypothesis of no long-run relationships among the underlined variables is:

\[ H_0 = \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \lambda_8 = 0 \]

The application of the ARDL approach involves three steps. The initial step is to determine whether long-run co-movement exists among the variables using the Ordinary Least Squares (OLS) method to estimate equation (8). The determination of long-run relationships among the underlined variables depends on the joint F-statistic. The estimated F-statistic is compared with two asymptotic critical value bounds. The lower value assumes that the explanatory variables are \( I(0), \) and the upper value assumes that the explanatory variables are \( I(1). \) If the estimated F-statistic is smaller than the lower critical bound value, there is no long-run relationship among the underlined variables. If the estimated F-statistic falls between both the lower and upper bound critical values, then the result is said to be inconclusive. Finally, the null hypothesis of no long-run relationship is rejected if the estimated F-statistic is greater than the upper bound critical value. After the cointegration has been established, the next step is to evaluate the long-run coefficients of the parameters in the model and draw conclusions from their predicted values. The long-run ARDL model \((m, q_1, q_2, q_3, q_4, q_5, q_6, q_7)\) is as follows:
A farmer to adaptive measures to lessen the effects of climate change. The literature, however, reveals that some farmers have factors that are unique to each farmer. Therefore, if farmers are rational, they are expected to implement measures to curb climate change impacts. Adaptive capacity tends to differ among farmers depending on several factors that are unique to each farmer, such as knowledge, availability, accessibility, use, and consultation. This study considered the following adaptation strategies: early maturing rice varieties; application of chemical or organic fertilizers; drought-tolerant rice varieties; improved irrigation; changing planting dates; farming near water bodies; mono-cropping; crop rotation; mixed cropping; the building of embankments; construction of fire belts; the shift from crop to livestock; change from farming to non-farming; and reduction in farm size.

The degree of smallholder farmers’ adaptive capacities was qualitatively determined by following Nakuja et al. (2012), Asante et al. (2012), Mabe et al. (2012), Ghosh et al. (2015), Eyasmin et al. (2017), and Akhtar et al. (2019), we measure smallholder farmers’ adaptive aptitudes to climate change by five factors: knowledge, availability, accessibility, use, and consultation. This study considered the following adaptation strategies: early maturing rice varieties; application of chemical or organic fertilizers; drought-tolerant rice varieties; improved irrigation; changing planting dates; farming near water bodies; mono-cropping; crop rotation; mixed cropping; the building of embankments; construction of fire belts; the shift from crop to livestock; change from farming to non-farming; and reduction in farm size.

The degree of smallholder farmers’ adaptive capacities was qualitatively determined by following Nakuja et al. (2012), Asante et al. (2012), Mabe et al. (2012), Ghosh et al. (2015), Eyasmin et al. (2017), and Akhtar et al. (2019). Further, rice-growers were required to specify the extent of attaining each factor. The lowest level of achievement each element or attribute is rated 0.25, whereas the highest level is assigned a score of 1. Likewise, a farmer who reaches a higher level in each feature is scored 0.75. The knowledge of adaptation strategies to adaptation strategy to minimize the consequences of climate change, the higher the degree to which a farmer, the farmer, can adapt to climate change effectively.

Table 3 illustrates how we measure each factor or attribute. The adaptive capacity index (ADCA) of an ith farmer to jth adaptation strategy is measured as:

$$ADCA_{ij} = \frac{KN_{ij} + US_{ij} + AV_{ij} + AC_{ij} + CU_{ij}}{N_i}$$

(11)

Where ADCAij indicates the adaptive aptitude of an ith farmer to a jth adaptation measure, KNij represents the knowledge of an ith farmer to a jth adaptive measure, USij is the usage level of jth adaptive measure by an ith farmer, AVij is the availability of innovations on jth adaptive measure to an ith farmer, ACij denotes the
accessibility of innovations on \( j \)th adaptive measure to \( i \)th farmer, \( CU_{ij} \) indicates the level of consultation of \( j \)th \( i \)th adaptive measure by an \( i \)th farmer, and \( N_i \) is the total of considered factors.

The ADCA of smallholder farmers is averagely calculated as follows:

\[
\text{avADCA}_j = \frac{\sum_{i=1}^{N} ADCA_{ij}}{N}
\]

(12)

where \( \text{avADCA} \) and \( N \) represent the average adaptive capacity of farmers and the number of observations, respectively.

Following the existing standards employed by previous studies (see Nelson et al 2010; Asante et al 2012; Mabe et al 2012; Nakuja et al 2012; Eyasmin et al 2017; Akhtar et al 2019), farmers’ adaptive aptitudes to climate change adaptation are categorised into low, moderate, and high. We measured the average adaptive capacities of each adaptation strategy and classified them into the three indices (high, moderate, and low). Table 4 presents smallholder farmers’ adaptive aptitudes to climate change adaptation.

From table 4, if the estimated adaptive capacity index falls within the range of \( 0 < ADCA_{ij} < 0.33 \), it implies that an \( i \)th farmer is lowly adaptive to a \( j \)th adaptive strategy. Besides, if the estimated adaptive capacity index falls within the bracket of \( 0.33 \leq ADCA_{ij} < 0.66 \), then the farmer is said to be moderately adaptive to a \( j \)th adaptive strategy. The range for high adaptive capacity is \( 0.66 \leq ADCA_{ij} \leq 1.00 \).

2.3.4. Analytical technique for the impacts of adaptive capacities on rice output

Following Mahmood et al (2012), Mabe et al (2012), and Eyasmin et al (2017), regression analysis is employed to compute the implications of adaptive capacities for rice production. The ordinary least squares (OLS) results are attained by estimating the log-log augmented Cobb-Douglas production function as expressed below:

\[
\ln QR_t = \lambda_0 + \psi_1 \ln X_t + \psi_2 \ln C_t + \mu_t
\]

(13)

Where \( \ln \) indicates natural logarithm and the notation \( \mu_t \) is the error term. The OLS computation procedures are simple and easy to comprehend relative to the other econometric techniques, hence being a choice analytical technique for this study. Most importantly, the OLS approach is commonly desirable due to its ease of use and strong statistical properties (Gauss–Markov theorem).

3. Empirical results and discussions

3.1. Results of the stationarity test

This section presents the stationarity test results. Table 5 shows the integrating orders of the concerned variables based on the Ng-Perron test. The results displayed in table 5 show that mean rainfall, rice production, mean temperature, rainfall variability, fertilizer consumption, temperature variability, the interaction term between temperature and precipitation, and energy consumption are stationary at their levels [i.e., \( I(0) \)]. Therefore, the stationarity test results affirm the suitability of the ARDL technique for this empirical analysis.

Table 3. Score levels of farmers’ attainment of attributes.

| Knowledge | Use | Availability | Accessibility | Consultation | Scores | Degree |
|-----------|-----|--------------|---------------|--------------|--------|--------|
| Very well | Several | Very Regular | Easily accessible | Several | 1.00 | Highest |
| Well      | Twice | Regular | Accessible | Twice | 0.75 | Higher |
| Fairly well | Once | Occasional | Not easily accessible | Once | 0.50 | High |
| Not well | Never | Never | Not accessible | Never | 0.25 | Low |

Source: Modified from Nakuja et al (2012), Asante et al (2012), Mabe et al (2012), Ghosh et al (2015), Eyasmin et al (2017), and Akhtar et al (2019).

Table 4. Degree of farmers’ adaptive capacities to climate change adaptation.

| Degree of ADCA | Ranges of indices for \( ADCA_{ij} \) | Ranges of indices for \( \text{avADCA}_j \) |
|---------------|---------------------------------|---------------------------------|
| High adaptive capacity | \( 0.66 \leq ADCA_{ij} \leq 1.00 \) | \( 0.66 \leq \text{avADCA}_j \leq 1.00 \) |
| Moderate adaptive capacity | \( 0.33 \leq ADCA_{ij} < 0.66 \) | \( 0.33 \leq \text{avADCA}_j < 0.66 \) |
| Low adaptive capacity | \( 0 < ADCA_{ij} < 0.33 \) | \( 0 < \text{avADCA}_j < 0.33 \) |

Source: Modified from Nakuja et al (2012), Asante et al (2012), Mabe et al (2012), Ghosh et al (2015), Eyasmin et al (2017), and Akhtar et al (2019).
3.2. Results of the ARDL cointegration test

The study conducted the ARDL bounds test to ascertain the presence of a long-run equilibrium association between rice output and its independent variables. Table 6 presents the outcomes of the ARDL bounds test. The computed F-statistic from the bounds test is compared with the lower and upper bound critical values to determine the cointegrating relationships among the variables. The findings show that the computed F-statistic (3.5647) exceeds the critical value of the upper bound (3.39). Thus, at the 5% threshold, we cannot reject the null hypothesis of no cointegrating relationships among the concerned variables. This result suggests a long-run equilibrium association between rice production and its independent variables.

3.3. Results of the long-run effects of climate change on rice production

This section presents the long-run results, and the estimated coefficients are displayed in Table 7. The evidence in Table 7 reveals that fertilizer consumption has a significant and positive effect on rice production in the long run. Thus, an increase in farmers’ utilization of fertilizers by 1% raises rice production by over 1.49% in Chengdu (China). This finding supports the results of Janjua et al. (2014), Chandio et al. (2018a),

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### Table 5. Results of the Ng-Perron unit root test.

| Variables | Lag | \( MZ_a \) | \( MZ_t \) | \( MSB \) | \( MP \) |
|-----------|-----|------------|------------|--------|--------|
| LNRCm | 5 | −44.561\(^a\) | −4.572\(^a\) | 0.103\(^a\) | 2.801\(^a\) |
| RAIN | 5 | −311.104\(^a\) | −12.470\(^a\) | 0.040\(^a\) | 0.297\(^a\) |
| RAV | 9 | −94.533\(^a\) | −6.874\(^a\) | 0.073\(^a\) | 0.971\(^a\) |
| TEMP | 5 | −59.073\(^a\) | −5.426\(^a\) | 0.092\(^a\) | 1.585\(^a\) |
| TEV | 9 | −93.396\(^a\) | −6.834\(^a\) | 0.073\(^a\) | 0.976\(^a\) |
| TEMP*RAIN | 5 | −253.333\(^a\) | −11.253\(^a\) | 0.044\(^a\) | 0.363\(^a\) |
| LNFERT | 1 | −77.500\(^a\) | −6.192\(^a\) | 0.080\(^a\) | 1.314\(^a\) |
| LNECON | 9 | −54.848\(^a\) | −5.237\(^a\) | 0.096\(^a\) | 1.662\(^a\) |

\(^a\) shows significance at the 1% level, whereas.

\(^b\) signifies that the critical values were sources from Table 1 of Ng and Perron (2001).

### Table 6. Results of the ARDL cointegration test.

| F-Statistic | Level of significance | Lower bound | Upper bound | Decision |
|-------------|----------------------|-------------|-------------|----------|
| 3.5647\(^a\) | 10% | 1.95 | 3.06 | Cointegrated |
| | 5% | 2.22 | 3.39 | |
| | 1% | 2.79 | 4.10 | |

\(^a\) indicates the rejection of the null hypothesis at a 5% level of significance.

### Table 7. Estimated long-run coefficients.

| Explanatory variables | Coefficient | Std. Error | t-Statistic | p-Value |
|-----------------------|-------------|------------|-------------|---------|
| Log of fertilizer consumption | 1.4918\(^a\) | 0.2125 | 7.0215 | 0.0000 |
| Log of energy consumption | 0.0995 | 0.2468 | 0.4034 | 0.6886 |
| Average rainfall | 0.1348\(^a\) | 0.0478 | 2.8186 | 0.0072 |
| Rainfall variability | −0.4691\(^a\) | 0.1617 | −2.9005 | 0.0058 |
| Average temperature | 0.5422\(^a\) | 0.2147 | 2.5257 | 0.0152 |
| Temperature variability | 0.9789 | 1.0675 | 0.9171 | 0.3641 |
| Interaction between temperature and rainfall | −0.0079\(^a\) | 0.0029 | −2.7815 | 0.0079 |
| Constant | −2.2002 | 4.3563 | −0.5051 | 0.6160 |

\(^a\) and \(^b\) indicate 1%, and 5% significance level, respectively

3.2. Results of the ARDL cointegration test

The study conducted the ARDL bounds test to ascertain the presence of a long-run equilibrium association between rice output and its independent variables. Table 6 presents the outcomes of the ARDL bounds test. The computed F-statistic from the bounds test is compared with the lower and upper bound critical values to determine the cointegrating relationships among the variables. The findings show that the computed F-statistic (3.5647) exceeds the critical value of the upper bound (3.39). Thus, at the 5% threshold, we cannot reject the null hypothesis of no cointegrating relationships among the concerned variables. This result suggests a long-run equilibrium association between rice production and its independent variables.

3.3. Results of the long-run effects of climate change on rice production

This section presents the long-run results, and the estimated coefficients are displayed in Table 7. The evidence in Table 7 reveals that fertilizer consumption has a significant and positive effect on rice production in the long run. Thus, an increase in farmers’ utilization of fertilizers by 1% raises rice production by over 1.49% in Chengdu (China). This finding supports the results of Janjua et al. (2014), Chandio et al. (2018a),
Chandio et al (2018b), Chandio et al (2020), and Pickson et al (2022), which show that fertilizers boost soil fertility of cultivated areas to enhance the growth and development of rice crops. Also, our results show that an increase in energy consumption positively affects rice production in the long run, but this is statistically insignificant. This finding indicates that energy consumption does not play any critical role in rice production in Chengdu in the long run. Ahsan et al (2020) confirmed no significant association between Pakistan’s energy usage and cereal production.

Average rainfall substantially and positively impacts rice cultivation in Chengdu, indicating that rainfall directly affects rice production in the long run. We find that rice production rises by 13.48 tonnes in the long run when the rainfall upsurges by 100 mm. Our finding supports the results obtained by previous studies (see Adedeji et al 2017; Attiaoui and Boufateh 2019; Sossou et al 2019; Pickson et al 2020) but contradicts Casemir and Diaw (2018), who indicated that mean rainfall did not affect the cultivation of grain crops in Benin. Pickson et al (2022) found no significant interaction between average rainfall and long-run rice production in China. Notwithstanding the positive impact of rainfall on rice production, the findings reveal that a rise in rainfall variability by an extent of deviation from the mean rainfall decreases rice cultivation in the long run by 0.47 tonnes, which is significant at the 1% level. This finding suggests that a surge in the extent of deviation from the mean precipitation in Chengdu is harmful to rice production. The long-run consequence of rainfall variability requires adaptation strategies to minimize the adverse effects of rainfall variability on rice cultivation in Chengdu. This finding contradicts Pickson et al (2020), who observed no significant association between rainfall variability and the cultivation of cereal crops in the long run. While Pickson et al (2020) focused on China as a whole, our findings contradict their study because we concentrated on Chengdu (the capital city of Sichuan province, China), with unique climatic conditions.

The results further show that mean temperature has a significant and positive influence on rice cultivation in the long term. Thus, mean temperature positively relates to rice cultivation in Chengdu. This outcome suggests that a 1 °C rise in mean temperature triggers the long-run rice production to surge by 0.54 tonnes. Akpalu et al (2008) and Bhandari (2013) reported similar observations for South Africa and Nepal (Dadeldhura District), although their estimated coefficient varies from our estimate, which is attributed to geographical differences. In contrast to previous studies (Adedeji et al 2017; Attiaoui and Boufateh 2019; Sossou et al 2019; Pickson et al 2020), our results show that average temperature has a positive relationship with the cultivation of cereal crops. Chandio et al (2020) and Pickson et al (2022) observed no significant association between average temperature and the cultivation of rice production in Pakistan and China, respectively.

To probe the impact of temperature further, we accounted for temperature variability in the model and found that it positively affects rice production in Chengdu (China). Specifically, our findings reveal that rice production in Chengdu increases by 0.98 tonnes with a one-standard-deviation rise in temperature variability. It is worth noting that, while the estimated coefficient is positive, it is not statistically significant when examined at the appropriate thresholds. This result implies that an increase in standard deviation from the mean temperature has no long-term significance. However, Pickson et al (2020) found that temperature variability adversely affects China’s grain production.

The study further indicated that the coefficient of the interaction term between temperature and rainfall is negative and significant at the 1% threshold. The implication is that when average rainfall increases by 1 mm, a 1 °C increment in average temperature will trigger a decline in rice production by 0.01 tonnes (i.e., 10 kilograms) in the long run. This outcome implies that the long-run positive effect of temperature on rice cultivation in Chengdu decreases as the pattern of rainfall increases.

3.4. Results of the short-run effects of climate change on rice production
This section presents the short-run estimations, and the results are displayed in table 8. The error correction term’s coefficient (~0.1539) is negative and significant at the 1% threshold. Thus, rice production will adjust by 15.4% of the previous year’s deviation from equilibrium in the short term. This outcome implies that the disequilibrium in the short run converges to long-run equilibrium with a slower speed of adjustment and may require approximately more than six years for stability to be restored. The F-statistic (11.7670) also affirmed the joint significance of the explanatory variables at a 1% level. The Durbin-Watson statistic of 2.2830 suggested no autocorrelation in the model. Table 8 shows the ARDL results for rice production and its regressors in the short run.

Again, the fertilizer consumption positively affected rice cultivation in the short term, which is substantial at the 1% threshold. With its coefficient of 0.2296, a 1% rise in fertilizer usage causes rice cultivation to upsurge by 0.23% in the short term. As the consumption of fertilizers rises, rice production is inclined to increase in the short run. A similar result is found in China (Pickson et al 2022). However, Chandio et al (2020) observed that, in the short run, the amount of fertilizer used in Pakistan has no substantial effect on rice cultivation.
Contrary to the long-run results, energy consumption recorded a positive sign, and it was statistically significant in explaining rice production in Chengdu in the short-run. Thus, rice production increases by 0.46% when energy consumption surges by 1% in the short run. This result shows that rice production in the short term rises when energy consumption improves. This paper affirms the findings of Ahsan et al. (2020), which indicates that energy usage directly influences the cultivation of cereal crops in Pakistan in the short run.

Besides, the short-run estimates show that the average rainfall coefficient is positive and significant at the 1% level. Thus, with its coefficient of 0.1388, when average rainfall increases by 100 mm, rice production will surge by 13.88 tonnes in the short run. This result agrees with the studies conducted by Eregha et al. (2014), Attiaoui and Boufateh (2019), and Sossou et al. (2019), which showed that precipitation has a positive relationship with rice cultivation. On the contrary, Abu et al. (2018) and Pickson et al. (2022) found no significant association between precipitation and rice production in Nigeria and China, respectively. Surprisingly, rainfall variability adversely affects rice production in Chengdu, which was statistically significant. The study reveals that rice production in the short-run declines by 0.3256 tonnes when the rainfall variability rises by an extent of deviation from the mean. This result means that rice production in Chengdu declines by 32.56 tonnes when rainfall variability increases by 100 mm, with a degree of variation from the mean rainfall in the short term.

Furthermore, the results revealed a statistically significant and positive association between mean temperature and rice cultivation in Chengdu in the short term. The study shows that rice production will increase by 0.67 tonnes as the average temperature increases by 1°C in the short run. This study contradicts the results obtained by Nyairo (2011), Abu et al. (2018), Attiaoui and Boufateh (2019), Sossou et al. (2019), and Chandio et al. (2020). According to Nyairo (2011), Abu et al. (2018), Sossou et al. (2019), and Pickson et al. (2020), there is a significant inverse association between temperature and cereal crop production. However, Pickson et al. (2022) reported that temperature has no significant effect on short-run rice production in China. Also, our study shows that temperature variability directly and significantly affects rice cultivation in the short term. This finding indicates that rice cultivation increases by 1.0414 tonnes in the short run as the temperature variability surges with an extent of deviation from the mean. Therefore, mean temperature and temperature variability are crucial factors explaining rice production in Chengdu.

The findings in table 8 show that the interaction term between temperature and rainfall has a negative coefficient, which is statistically significant at the 1% threshold in the short run. This result suggests that temperature contributes negatively to rice cultivation in Chengdu only when rainfall increases. We noticed that the long-run impact of the interaction term between temperature and precipitation on rice production is similar to its short-run implications. When average rainfall rises by 1 mm, a 1°C increase in average temperature will cause rice production to decrease by 0.01 tonnes (i.e., 10 kilograms) in the short run.

3.5. Results of the diagnostic and stability tests for the ARDL model

We present the suitability and consistency of the ARDL model by applying diagnostic and stability tests. These tests help avoid spurious results and validate the estimated model’s statistical adequacy to make relevant inferences. Table 9 presents the outcomes of the diagnostic and stability tests.
The various diagnostic and stability test results showed no problems with autocorrelation, heteroscedasticity, functional specification, and normality in the model. The tests affirmed the statistical adequacy of the estimated model. The plots of CUSUM and CUSUMSQ, as shown in figures 2 and 3 in that order, indicate the coefficients of the ARDL model are stable at the 5% level of significance.
### Table 10. Degree of farmers’ adaptive capacities to adaptation strategies.

| Adaptation strategies                  | Adaptive capacity | Rank | Degree of adaptive capacities          |
|----------------------------------------|-------------------|------|-----------------------------------------|
| Early maturing rice varieties          | 0.88              | 1    | High adaptive capacity                  |
| Use of organic or chemical fertilizers | 0.82              | 2    | High adaptive capacity                  |
| Improved irrigation                    | 0.76              | 3    | High adaptive capacity                  |
| Farming near water bodies              | 0.72              | 4    | High adaptive capacity                  |
| Mono-cropping                          | 0.67              | 5    | High adaptive capacity                  |
| Crop rotation                          | 0.65              | 6    | Moderate adaptive capacity              |
| Mixed cropping                         | 0.65              | 6    | Moderate adaptive capacity              |
| Drought-tolerant rice varieties        | 0.60              | 7    | Moderate adaptive capacity              |
| Building of embankments                | 0.55              | 8    | Moderate adaptive capacity              |
| Changing planting dates                | 0.54              | 9    | Moderate adaptive capacity              |
| Construction of fire belts             | 0.50              | 10   | Moderate adaptive capacity              |
| Change from farming to non-farming     | 0.32              | 11   | Low adaptive capacity                   |
| Change crop to livestock               | 0.31              | 12   | Low adaptive capacity                   |
| Integration of trees in rice farms     | 0.30              | 13   | Low adaptive capacity                   |
| Reduce farm size                       | 0.29              | 14   | Low adaptive capacity                   |
| Average adaptive capacity              | 0.57              |      | Moderate adaptive capacity              |

Source: Authors’ construction using field data, 2019.

### 3.6. Smallholder farmers’ adaptive capacities to climate change adaptation strategies

Table 10 presents rice farmers’ adaptive capabilities in connection with the various adaptation strategies. The results indicated that farmers are highly adaptable to using early maturing rice varieties, organic or chemical fertilizers, improved irrigation, farming near water bodies, and mono-cropping. This is shown by their adaptive aptitudes being within the bracket of $0.66 \leq ADCA_f \leq 1$. Considering these adaptation measures with high adaptive aptitudes, mono-cropping and early maturing rice varieties reported the lowest and highest adaptive aptitudes of 0.67 and 0.88, respectively. Besides, the adaptive aptitudes for using organic or chemical fertilizers, improved irrigation, and farming near water bodies are 0.82, 0.76, and 0.72, respectively.

The findings also show that farmers are moderately adaptable to crop rotation, mixed cropping, drought-tolerant rice varieties, the building of embankments, changing planting dates, and the construction of fire belts. Out of the fifteen (15) adaptive practices adopted, the farmers were moderately adaptive to six (6). The practice of mixed cropping and crop rotation recorded the highest adaptive aptitude value of 0.65, considering the adaptive measures with which farmers were moderately adaptive. In contrast, the practice of constructing fire belts recorded the lowest adaptive capacity score of 0.50. The adaptive capacities for drought-tolerant rice varieties, the building of embankments, and changing planting dates were estimated as 0.60, 0.55, and 0.54, respectively.

The results further show that the rice farmers in Chengdu have a low adaptive capacity to the change from farming to non-farming, the transition from crop to livestock, the integration of trees in rice farms, and the reduction in farm size. The shift from farming to non-farming has an adaptive ability score of 0.32. The adaptive ability scores computed for the change of crop to livestock, the integration of trees in rice farms, and the reduction in farm size are 0.31, 0.30, and 0.29, correspondingly. Taking everything into account, the average adaptability of the farmers was 0.57, which means that smallholder rice farmers in Chengdu are only moderately adaptable to climate change. Given that farmers can moderately adapt to climate change, they should be encouraged to improve their ability to adapt to the changing climatic conditions.

### 3.6.1. Percentage of the degree of smallholder farmers’ adaptive capacities

Table 11 shows the proportions of the extent of adaptive capabilities to climate change adaptation among smallholder farmers. We discovered that 151 farmers who participated in the study are high adapters to climate change adaptation measures, representing 39.4% of the 383 farmers sampled. Also, 144 (37.6%) farmers are moderate adapters to climate change. On the contrary, 88 (23%) farmers have a low adaptive capacity for climate change adaptation strategies. Although most rice farmers (39.4%) are high adapters to climate change adaptation strategies, the surveyed farmers are moderate adapters to climate change adaptation strategies on average. This is shown by the estimated average adaptive capability of 0.55, which lies within the bracket of $0.33 \leq \bar{ADCA}_f \leq 0.66$ (that is, moderate adaptive ability). The finding indicates that, on average, the farmers do not yet possess all the resources needed to respond appropriately to the changing climatic conditions (see Charles and Rashid 2007; Mabe et al 2012; Ghosh et al 2015; Eyasmin et al 2017; Akhtar et al 2019).
Table 11. Proportions of the level of adaptive capacities of rice-growing farmers.

| Adaptive capacity | Mean adaptive capacity | Frequency | Percentage |
|-------------------|------------------------|-----------|------------|
| High Adapters     | 0.77                   | 151       | 39.4       |
| Moderate Adapters | 0.58                   | 144       | 37.6       |
| Low Adapters      | 0.31                   | 88        | 23         |
| Average           | 0.55                   | 383       | 100        |

Source: Authors’ construction using field data, 2019.

Table 12. Contingency coefficient test for multicollinearity between the explanatory variables.

| AGE     | INCO  | HHS  | LAC  | HAC  | CAP  | FBO  | EDU  | AEXT | LAB  |
|---------|-------|------|------|------|------|------|------|------|------|
| AGE     | 1     |      |      |      |      |      |      |      |      |
| INCO    | −0.047| 1    |      |      |      |      |      |      |      |
| HHS     | 0.014 | 0.255a| 1    |      |      |      |      |      |      |
| LAC     | 0.066 | 0.125a| 0.084| 1    |      |      |      |      |      |
| HAC     | 0.106 | 0.246a| 0.133| −0.472a| 1    |      |      |      |      |
| CAP     | −0.087| 0.177a| 0.034| 0.021| 0.153a| 1    |      |      |      |
| FBO     | −0.051| 0.064 | 0.018| −0.123a| −0.214a| 1    |      |      |      |
| EDU     | −0.501a| 0.087| 0.085| 0.065| 0.062| 0.076| 0.033| 1    |      |
| AEXT    | 0.075 | 0.078 | .141a | .372a | .286a | .128a | −0.082 | 0.051 | 1    |
| LAB     | 0.085 | −0.071| −0.074| −0.120a| −0.154a| −0.127a| −0.009 | −0.022 | −.102a| 1    |

*AGE* is the age of the household head, *INCO* indicates the monthly household income, *HHS* represents the household size, *LAC* denotes low adaptive capacity, *HAC* represents high adaptive capacity, *CAP* shows capital stock, *FBO* indicates farmer-based organization membership, *EDU* connotes educational attainment of household head, *AEXT* notes agricultural extension service, and *LAB* represents farm labour. Also, * signifies weak collinearity between the two variables.

3.7. Regression analysis of the smallholder farmers’ adaptive capacities as determinants of rice output

Hitherto the empirical analysis of the impacts of farmers’ adaptive capabilities to climate change adaptation measures on rice output in Chengdu, diagnostic tests were performed to ensure that the regression results were consistent and unbiased. The diagnostic tests involved multicollinearity using the contingency coefficient test and variance inflation factor, the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity, and the Ramsey specification-error test for omitted variables. We applied the contingency coefficient test and variance inflation factor (VIF) to determine whether there is evidence of multicollinearity between the explanatory variables. Multicollinearity involves the existence of associations between the independent variables. In extreme instances of perfect association between the explanatory variables, multicollinearity can imply that an idiosyncratic least-squares estimation cannot be conducted for regression analysis (Field 2009).

‘Multicollinearity expands the standard errors and confidence intervals, leading to unreliable results of specific explanatory variables’ (Belsley et al 1980). From the contingency coefficient test results, as shown in table 12, all the regressors were considered in the estimation since none of the regressors was strongly correlated.

As a robust check on the results of the contingency coefficient test, the values of VIF were generated. According to Sekaran and Bougie (2009), a VIF value that is ten or more than ten (VIF ≥ 10) suggests the existence of multicollinearity between the explanatory variables. The results indicated no problem with multicollinearity between the explanatory variables. In other words, the data did not show extreme correlations between the explanatory variables because VIF values for all variables ranged from 1.087 to 5.508. The VIF values for household head’s age (1.403), educational attainment (1.379), household size (1.120), monthly household income (1.200), farm labour (1.056), capital stock (1.168), agricultural extension service (4.646), farmer-based organization membership (1.087), low adaptive capacity (5.508), and high adaptive capacity (2.090) are given in table 13.

3.8. Heteroscedasticity

The study determined whether the model was heteroscedastic using the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity. Table 14 shows the result of the Breusch-Pagan/ Cook-Weisberg test for heteroscedasticity.
The result presented in table 14 shows that the model has a probability value of 0.1406, suggesting we cannot reject the null hypothesis of homoscedasticity. Thus, the residual error has a constant variance, and the model is free from heteroscedasticity.

3.9. Omitted variable test
The study deployed the Ramsey regression specification-error test for an omitted variable to establish whether the model requires additional variables. Table 15 displays the result of the Ramsey regression specification-error test for omitted variables.

Table 14. Breusch-Pagan/Cook-Weisberg heteroscedasticity test result.

| Breusch-Pagan / Cook-Weisberg test for heteroskedasticity |
|----------------------------------------------------------|
| Ho: Constant variance |
| Variables: fitted values of ln(rice output) |
| Chi-square (1) = 2.17 |
| Prob > Chi-square = 0.1406 |

Table 15. Ramsey regression specification-error test result (for omitted variables).

| Ramsey RESET test using powers of the fitted values of ln(rice output) |
|-------------------------------------------------|
| Ho: model has no omitted variables |
| F(3, 369) = 0.94 |
| Prob > F = 0.4208 |

The result presented in table 14 shows that the model has a probability value of 0.1406, suggesting we cannot reject the null hypothesis of homoscedasticity. Thus, the residual error has a constant variance, and the model is free from heteroscedasticity.

3.9. Omitted variable test
The study deployed the Ramsey regression specification-error test for an omitted variable to establish whether the model requires additional variables. Table 15 displays the result of the Ramsey regression specification-error test for omitted variables.

The result in table 15 shows that the probability value of the model is greater than the appropriate threshold (i.e., the 0.05 level of significance). This result implies that the model has no omitted variables, and it can be considered in discussing policy options.

Table 16 presents the findings of the OLS regression on the impacts of the small-scale farmers’ adaptive aptitudes to climate adaptation on rice output. These findings were attained by the log-log augmented production function expressed in equation (13). The R-squared is 0.867, which implies that 86.7% of changes in rice output are explained by variations in educational attainment, household head’s age, household size, monthly household income, farm labour, capital stock, agricultural extension service, farmer-based organization, low adaptive capacity, and high adaptive capacity. The F-Statistic (3.53), with a p-value of 0.000, suggests that all the explanatory variables in the model are jointly significant.

From the results presented in table 16, the age of the household head has a positive relationship with rice output in Chengdu. This study implies that a 1% rise in the age of the household head can result in a 0.13% increase in rice output. However, the positive impact of the household head’s age was statistically insignificant. Thus, the age of the household head does not significantly influence rice output in the study area. Eyasmin et al (2017) found no significant link between the age of the household head and the amount of rice produced in Bangladesh’s Pabna District. In addition, we found that farmers’ involvement in farm-based organizations is significant in determining rice output. A coefficient of 0.101 implies that participation in farmer-based organizations has a significant positive effect on the amount of rice produced in Chengdu. The plausible reason
is that participation in farmer-based organisations favours modern farming innovations and technologies to increase rice productivity (see Abebaw and Haile 2013).

Education enhances farmers’ attitudes to gaining knowledge on different aspects of farming, and it increases farmers’ capacity to observe and understand a critical situation. Our results show that the household head’s educational attainment is significant and positively related to rice output. This result implies that an increase of a year of education by farmers will result in a 0.06% increase in rice output. This finding supports Deressa et al. (2009), who pointed out that highly educated farmers tend to adapt better to the changing climatic conditions and, as a result, increase their rice output. Besides, the number of farm labourers engaged has a significant and direct association with rice output in Chengdu. With its coefficient of 0.028, rice output will increase by 0.03% due to a 1% rise in the number of labourers engaged, all the other factors being held constant. This outcome agrees with Mabe et al. (2012) for the Northern Region of Ghana and Eyasmin et al. (2017) for the Pabna District in Bangladesh, who found a positive association between farm labour and rice output.

The study revealed that monthly household income has a significant and positive effect on rice cultivation in Chengdu. With its coefficient of 0.083, an increase in the monthly household income would increase rice production by 0.08%, all other factors being constant. The results also indicate that household size positively and significantly relates to rice production at the 5% level. This result implies that an increase in household size will improve 0.136% in rice output in Chengdu. In addition, the capital stock did not meet its expected sign. The negligible effect of capital on rice output is consistent with the results obtained by Mabe et al. (2012) and Eyasmin et al. (2017) for the Northern Region of Ghana and the Pabna District in Bangladesh, respectively.

Moreover, access to agricultural extension services has a significant and beneficial effect on rice production in Chengdu. By implication, a rise in the unit change in extension service increases rice output by 0.25 units, considering all other inputs constant. The extension service provides farmers with information about new agricultural and adaptive innovations (Banjade 2003; Katungu 2007) to lessen the impacts of climate change on their livelihoods. Deressa et al. (2009) also reported that extension services help farmers effectively adapt to the consequences of climate change.

The results further show that farmers with a high adaptive capacity to climate change obtain more rice output than farmers with a low adaptive capacity who gain less rice output. Thus, farmers’ adaptive capabilities significantly affect rice production. From the findings, the more a farmer can adapt to climate change, the greater the rice yield a farmer will obtain.

The decline in rice output by lowly adaptive farmers has to do with their lack of knowledge and skills related to farming in adapting to climate change. Our findings support the idea that highly adaptive farmers can use modern technologies to alleviate the effects of climate change on their crops. Mabe et al. (2012) and Eyasmin et al. (2017) found similar results in the Northern Region of Ghana and the Pabna District of Bangladesh, respectively.
4. Concluding remarks and policy implications

Climate change is expected to affect China’s rural farming communities severely. For this reason, the country has launched several adaptation strategies geared toward addressing its farmers’ needs. Nevertheless, adaptation is strongly reliant on the adaptive capacity of a system, region, or community to withstand the destructive effects of climate change. Using Chengdu as a case study, we examined the impacts of climate change and smallholder farmers’ adaptive capacities on rice production. This study is broadly divided into two parts that are distinct but connected. The first part used the autoregressive distributed lag (ARDL) model to assess the effects of climate change on rice production in Chengdu (China), covering the period 2000Q1-2016Q4. We show that mean rainfall and temperature induce rice production positively in the long and short run. While temperature variability has no significant impact on long-run rice production, it positively influences short-run rice production in Chengdu. Rainfall variability and the interaction term between temperature and precipitation are detrimental to rice production in the long and short run. The results reveal that fertilizer application and energy consumption inputs play a critical role in supporting rice production. However, the impact of energy consumption is substantial in the short run.

The second part provided a new perspective on smallholder farmers’ adaptive capacities to climate change in rice production. Based on a survey of 383 rice growers in Chengdu, the results show that farmers’ adaptive capabilities significantly affect rice production. From the findings, the more a farmer can adapt to climate change, the greater the rice yield a farmer will obtain. Also, our results show a positive relationship between rice output and the control variables (educational attainment, household size, monthly household income, the number of farm labourers engaged, participation in farmer-based organizations, and access to extension services).

The findings of this study are important to policymakers as they can help them develop effective policies and interventions that can help improve the adaptive capabilities of small-scale farmers to climate change. This study also highlights the various policy implications to help small-scale farmers increase their rice production in Chengdu. The study revealed that the average rice farmer in Chengdu does not have the necessary resources to adapt to the changing climate conditions. Therefore, policymakers should develop policies that will help improve farming households’ adaptive capacities. To increase farmers’ ability to adapt to climate change, policymakers in Chengdu (China) should also implement policies that will help them use adaptation measures effectively. This can be done by establishing extension programmes that will help them improve their farming practices. Such a policy intervention will provide small-scale farmers with the necessary tools and resources to increase their rice production.

Finally, this research does have limitations. Rice was the only crop considered in examining the effects of climate change and smallholder farmers’ adaptive capabilities on crop production. Therefore, future research needs to assess farmers’ adaptive capabilities and climate change impacts on maize, wheat, vegetables, sugarcane, sweet potatoes, grapes, peaches, and tea. Also, a study of how individual smallholder farmers adapt to climate change and an analysis of how much it costs to adapt to climate change would be vital in figuring out the most cost-effective way to make smallholder farmers less vulnerable to the destructive effects of climate change.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Competing interests

The authors declared no conflict of interest.

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Ethical approval

Academic ethics codes and policies guided this study. The anonymity of the key informants was preserved, and any information provided by respondents was kept with the utmost confidentiality.

Consent to participate

Participants of the household survey assented to the consent form before the data collection.

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