Implications of Climate Change on Food Security in Zimbabwe: Developing Resilient and Sustainable Cereal Production

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ABSTRACT

Climate change has had detrimental effects on agricultural productivity in developing nations, particularly affecting cereal crop production in Zimbabwe. This study utilized the Autoregressive Distributed Lag (ARDL) model approach with co-integration and an error correction term to investigate these impacts. The ARDL method was chosen for its ability to handle non-stationary data and provide unbiased estimates of long-run coefficients. The findings from the estimated model confirm a sustained relationship between cereal crop production, climate change variables (specifically temperature and precipitation), and other explanatory factors. Precipitation was found to positively and significantly influence cereal crop production in both the short and long terms, whereas temperature changes had a significant negative impact. Over the long term, cereal crop production benefited significantly from factors such as arable land availability, fertilizer usage, and carbon dioxide emissions, while in the short term, labor force participation positively affected production. These results underscore the importance of developing cereal crop varieties resilient to higher temperatures and strengthening initiatives like the Climate Resilient Programmes. Collaborative efforts among nations are crucial for mitigating the adverse effects of climate change on agriculture globally.

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1. Introduction and Background

Climate change poses a significant threat to global food security, with its impacts being especially severe in developing countries. Zimbabwe, a country heavily reliant on agriculture, particularly cereal production, is highly vulnerable to the adverse effects of climate change. The Intergovernmental Panel on Climate Change (IPCC) has reported that increasing temperatures, changing precipitation patterns, and the frequency of extreme weather events are expected to reduce agricultural yields in many parts of Africa, including Zimbabwe (IPCC, 2019). The country's cereal production, which includes crops such as maize, sorghum, and millet, is crucial for both food security and economic stability. However, climate change threatens to disrupt these vital agricultural systems, exacerbating food insecurity and poverty (FAO, 2020).

Increasing frequencies of extreme weather events, particularly droughts, threaten the country's food security. For instance, the 2023/24 season experienced a severe drought which has since been declared a national disaster. There is evidence of a changing climate in Zimbabwe, demonstrated by declining rainfall trends and increasing temperatures (see Figures 1a and b). Given the positive association between cereal production and rainfall (see Figure 2a), there has been a declining production of cereals in Zimbabwe (see Figure 2b). This trajectory is not good for the future of food security in the country. Business as usual will lead to severe food shortages and widespread hunger in the future. Strategies for climate-proofing agriculture are therefore critical to climate change-induced food insecurity.

Figure 1a. Annual rainfall.

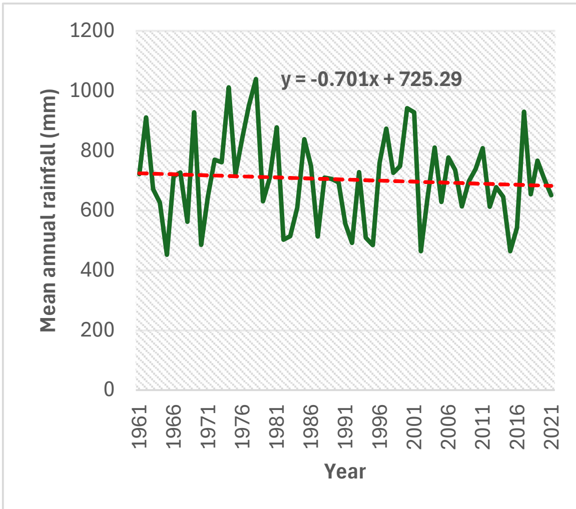
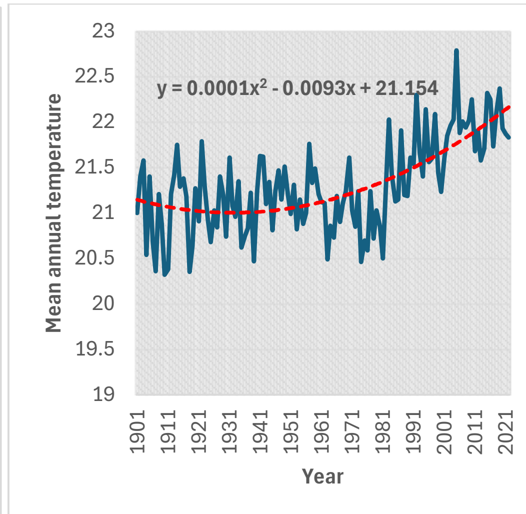


Figure 1b. Annual temperature.



Source: Authors' demonstration

Figure 2a. Cereal production and rainfall.

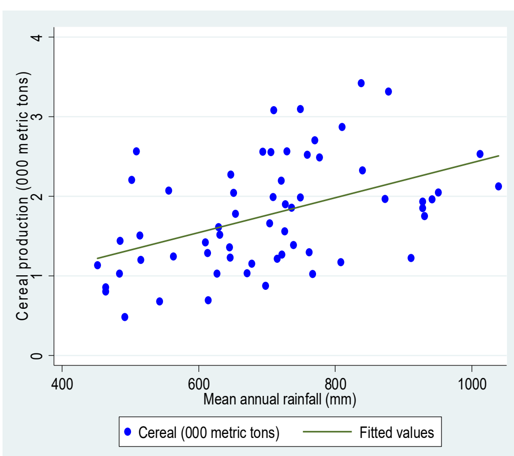
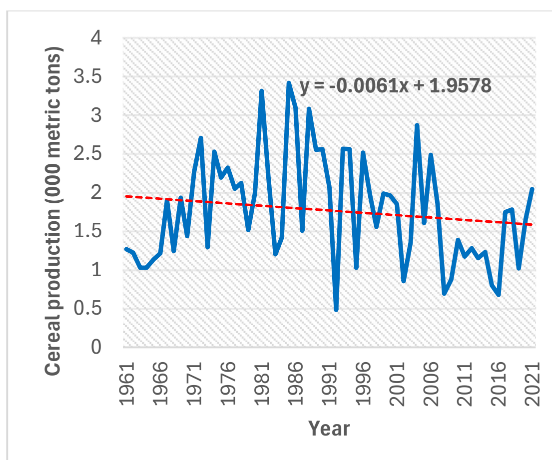


Figure 2b. Cereal production trend.



Source: Authors' demonstration.

Recent studies have shown that Zimbabwe has already experienced significant climate variability, leading to recurrent droughts and floods that severely affect cereal production (Brown et al., 2021; Muzari et al., 2022). These climatic events not only reduce crop yields but also lead to increased post-harvest losses, further threatening food availability. Additionally, the economic and infrastructural challenges in Zimbabwe, such as limited access to modern farming technologies and financial resources, hinder the adaptation and resilience of its agricultural sector (UNDP, 2018). As a result, the country's ability to achieve sustainable food security in the face of climate change is critically compromised.

The objectives of this study are multifaceted. First, it aims to analyze the specific impacts of climate change on cereal production in Zimbabwe. Second, the study seeks to evaluate the existing adaptive measures and their effectiveness in mitigating the adverse effects of climate change on cereal production. Third, the study will develop recommendations for enhancing the resilience and sustainability of cereal production systems. This involves exploring innovative agricultural practices, improving access to climate-resilient seeds, and advocating for policy changes that support sustainable agriculture. Ultimately, the goal is to contribute to the development of a more resilient agricultural sector that can ensure food security in Zimbabwe despite the challenges posed by climate change.

2. Literature

The nexus of climate change and food security presents one of the most urgent global challenges of our time. The implications of climate change on food security are multifaceted, involving complex interactions between environmental, economic, and social systems. This literature review aims to synthesize both theoretical and empirical research on the impacts of climate change on food security, with a specific focus on developing resilient and sustainable cereal production systems.

The concept of food security, as defined by the Food and Agriculture Organization (FAO), encompasses four main dimensions: availability, access, utilization, and stability (FAO, 2018). Climate change affects these dimensions in various ways. Theoretical frameworks suggest that climate change, characterized by rising global temperatures, changing precipitation patterns, and an increase in the frequency and intensity of extreme weather events, poses significant threats to agricultural productivity and, consequently, to food security (IPCC, 2021).

Cereal crops, including wheat, rice, and maize, are fundamental to global food security. These crops are not only dietary staples for billions of people but also critical to economic stability in many regions. The theoretical literature highlights several mechanisms through which climate change impacts cereal production. Increased temperatures can accelerate crop maturation, shorten growing periods, and increase evapotranspiration rates, all of which can lead to reduced yields (Lobell & Gourdji, 2012). Altered precipitation patterns can result in droughts or excessive rainfall, both detrimental to crop health and productivity. Drought stress can severely limit water availability for crops, while excessive rainfall can cause waterlogging and promote crop diseases (Rosenzweig et al., 2014). Furthermore, the rising frequency of extreme weather events, such as hurricanes, heatwaves, and floods, poses direct threats to crop survival and yields (Lesk, Rowhani, & Ramankutty, 2016).

To address these challenges, building resilience and sustainability in agricultural systems is crucial. Resilience in agriculture refers to the capacity to absorb and recover from shocks and stresses, such as those induced by climate change, while maintaining functionality. Sustainable agriculture aims to meet current food needs without compromising the ability of future generations to meet their own needs (Altieri, Nicholls, & Montalba, 2017). Theoretical approaches to enhancing resilience and sustainability in cereal production emphasize adaptive management practices, crop diversification, and the use of climate-resilient crop varieties. Agroecological principles, which focus on biodiversity, soil health, and ecological interactions, are also essential for fostering resilience and sustainability in agricultural systems (Altieri, Nicholls, & Montalba, 2017).

Empirical studies provide substantial evidence of the adverse impacts of climate change on cereal production. For instance, Lobell et al. (2011) analyzed data from major cereal-producing regions and found that global maize and wheat production had decreased due to temperature increases from 1980 to 2008. Similarly, Zhao et al. (2017) conducted a meta-analysis and concluded that for each degree Celsius increase in global temperature, average global yields of wheat, rice, and maize could decline by 6.0%, 3.2%, and 7.4%, respectively. In Africa, Schlenker and Lobell (2010) projected that climate change could reduce cereal crop yields by 20-30% by 2050, with the most significant impacts in sub-Saharan Africa. Their study highlighted that smallholder farmers, who rely heavily on rain-fed agriculture, are particularly vulnerable to climate change.

Adaptation strategies are critical for mitigating the impacts of climate change on cereal production. Empirical research has identified several effective adaptation strategies. Improved crop varieties, particularly those that are drought-tolerant and heat-resistant, are crucial for maintaining yields under changing climate conditions. Cairns et al. (2013) reviewed progress in breeding maize for drought tolerance in sub-Saharan Africa and found significant yield improvements in drought-prone areas. Efficient water use and irrigation practices can also mitigate the effects of altered precipitation patterns. Studies by Fereres and Soriano (2007) demonstrated that deficit irrigation, which optimizes water use, can maintain crop yields while conserving water resources.

Agroforestry and soil management practices play a vital role in enhancing resilience. Integrating trees and shrubs into agricultural systems (agroforestry) and improving soil health through organic amendments and conservation tillage can bolster crop resilience. Mbow et al. (2014) showed that agroforestry practices in Africa improved soil fertility and crop yields while providing additional ecosystem services. Crop diversification and rotation are also essential strategies. Diversifying crops and implementing crop rotation can reduce risks associated with climate variability and pest outbreaks. Lin (2011) found that diverse cropping systems are more resilient to climate extremes and can maintain higher yields compared to monocultures.

Early warning systems and climate services are critical for providing farmers with timely information to make informed decisions about planting and harvesting. Hansen et al. (2011) reviewed the effectiveness of climate services in agriculture and highlighted their potential to improve farm management and reduce climate risks. For instance, providing accurate and timely weather forecasts can help farmers plan irrigation, pest control, and other management practices more effectively, thereby reducing crop losses and improving yields.

Several case studies illustrate the successful implementation of adaptation strategies to build resilience in cereal production. In India, Aggarwal et al. (2018) studied the adoption of climate-smart agricultural practices, such as stress-tolerant crop varieties, precision farming, and integrated nutrient management. They found that these practices increased cereal yields and farm incomes while reducing greenhouse gas emissions. In Ethiopia, Tesfaye et al. (2016) evaluated the impact of climate change adaptation strategies on cereal production. Their findings indicated that adopting improved crop varieties, soil and water conservation practices, and agroforestry significantly enhanced crop productivity and resilience. In Zimbabwe, Zhakata et al. (2020) analyzed the effectiveness of conservation agriculture in maize production. Their study revealed that conservation agriculture practices, including minimum tillage, crop rotation, and mulching, improved soil health and maize yields, particularly under drought conditions.

3. Methodology

3.1 Data Sources

The study utilized a 32-year time series dataset for Zimbabwe, covering the period from 1980 to 2022. This data was sourced from the World Bank's World Development Indicators, FAOSTAT, and the Zimstat.

3.2 Model specification

The primary objective of the study is to investigate the climate change on cerial production in Zimbabwe. The choice of variables was guided by Jiang (2020) and Pickson et al., (2023). Empirically, the model is expressed as follows:

$$lnCP_t = \beta_0 + \beta_1 lnCO_{2t} + \beta_2 lnAL_t + \beta_3 lnFert_t + \beta_4 lnTemp_t + \beta_5 Prec_t + \beta_5 LFPR_t + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where ln CP_t − is the logarithm of cereal crops produced, $lnCO_{2t}$− the logarithm of carbon dioxide emission, $lnAL_t$ is the logarithm of arable land used for cultivation of crops, $lnFert_t$ is the logarithm of the amount of fertilizer consumed per arable land, $lnTemp_t$ is the logarithm of annual temperature change, $lnPrec_t$ the natural logarithm of precipitation and $LFPR_t$ is the laborforce participation. β_0 is the constant, $\beta_1 \ldots\ldots.. \beta_6$ are parameters. Finally, u_t is a random error term.

From equation (1) the ARDL model of the study is given as follows:

$$\Delta CP_t = \propto + \sum_{i-1}^{p} \propto_{1t} \Delta CO_{t-1} + \sum_{i-0}^{q} \alpha_{2i} \Delta AL_{t-1} + \sum_{i-1}^{q} \alpha_{3i} \Delta gFert_{t-1} + \delta_1 Temp_{t-1} + Prec_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

where; $increment\ is$ the first difference operator and ε is the error term. In equation (2), credit to the private sector is expressed in terms of its lagged value, the current and lagged values of the control variables.

The ARDL applies to this study as it is effective for a sample under a small-time frame. In addition, the ARDL method provides robust results for both short-run and long-run relationships simultaneously without losing any long-run information. Most importantly, unit root tests and diagnostic tests like lag length selection criteria were done before estimating the model to avoid a spurious regression.

The ARDL model contains the lagged value (s) of the dependent variable, and the current and lagged values of the regressors as explanatory variables (Pesaran *et al*., 2001). In addition, the ARDL uses a combination of endogenous and exogenous variables, unlike the VAR model which is strictly for endogenous variables. The ARDL is associated with several advantages. The model can be specified when variables become stationary without differencing, integrated of order zero *I(0)* and when variables become stationary after first differentiation, integrated of order one *I(1)*. However, the model cannot be specified if variables become stationary after the second differentiation, integrated of order two *I(2)*. In addition, (Pesaran, Shin and Smith, 1997) indicated that the model can be specified irrespective of whether the variable is *I(0)*, *I(1)* or fractionally co-integrated. Unlike having a multiple equation to estimate as in the case of the VAR model, the ARDL is associated with a single-equation set-up, which makes it simple to implement and interpret.

Furthermore, different variables can be assigned different lag lengths as the model is entered. The ADRL technique is free from residual correlation since variables stand as a single equation, thus it is easy to derive the Error Correction Model (ECM) from simple linear transformation by integrating short-run adjustments with long-run equilibrium without loss of information. In addition, this approach as well takes a sufficient number of lags to capture the data-generating process in a dynamic framework of general-to-specific modelling framework. Moreover, the Error Correction Term (ECT) which integrates short-run adjustments with long-run equilibrium without losing long-run information, can be derived from ARDL through a simple linear transformation.

The number of lags to use will be verified by the Akaiki Information Criterion (AIC), the Schwarz Information Criterion (SIC) and the Hannan-Quinn Information Criterion (HQ).

The generalized ARDL (p, q) model is specified as:

$$\boldsymbol{Y}_t = \gamma_{0i} + \sum_{i=1}^{p} \delta_i \boldsymbol{Y}_{t-1} + \sum_{i=0}^{q} \beta_i' X_{t-i} + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (3)$$

where; $\boldsymbol{Y}_t'$ is a vector and the variables in $(\boldsymbol{X}_t')'$ is

allowed to be purely *1(0)* or *I(1)* or co-integrated; β and δ are coefficients; γ is the constant; $i = 1, \dots, k$; p, q are optimal lag orders; ε_{it} is a vector of error terms – observable zero mean white noise vector process (serially uncorrelated or independent).

4.Findings and Discussion

4.1 Result of the Stationarity Test.

Before estimating the model, it is essential to confirm that the variables in the equation are stationary, as some variables exhibit significant variability over time. This requires determining their order of integration. The study assessed the stationarity of the chosen variables at their levels or first differences. The Augmented Dickey-Fuller (ADF) test was employed for this purpose, and the results are presented in Table 1.

Table 1: Stationarity test

Variables	ADF at level		ADF at 1st differ	
	Z (*t*)-statistics	*P* value for *Z* (*t*)	Z (*t*)-statistics	*P* value for *Z* (*t*)
lnCP	0.119	0.9673	−6.569***	0.0000
lnTemp	−2.461	0.1254	−4.205***	0.0006
lnPrec	−2.354	0.1552	−6.441***	0.0000
$lnCO_2$	0.628	0.9883	−4.309***	0.0004
lnAL	−0.659	0.8571	−3.164**	0.0222
lnFert	−1.852	0.3552	−6.170***	0.0000
LFPR	−2.135	0.2307	−3.621***	0.0054

Source: Authors Computations (2024)

The result shows the variables are stationary at their first difference I (1).

4.2 ARDL Bounds Testing for Co-Integration.

In order to empirically analyze the long-run relationships and short-run dynamic interactions among the variables (cereal crop production, fertilizer, carbon dioxide emissions, arable land, temperature, precipitation, and labor force participation rate), the ARDL bounds test to cointegration techniques was applied. The ARDL long-run co-integration outcomes, the results show the existence of long-run cointegration relationships among the production of cereal crops and explanatory variables.

4.3 Long-Run Coefficients and Short-Run Dynamics.

To test for the short-run relationship, the model estimates the ARDL model and the results are presented in table below.

Table 2: The estimated results of the ARDL model (long- and short-run coefficients).

Variables	Coefficient	Std. err.	*t*-statistics	$P > \lvert t \rvert$
Estimated long-run coefficients				
$\ln CO_2$	0.2314***	0.0848	2.73	0.016
lnAL	1.6187***	0.3449	4.69	0.000
lnFert	0.3395***	0.0872	3.89	0.002
lnTemp	−1.1234*	0.5644	−1.99	0.066
lnPrec	0.1653**	0.0688	2.40	0.031
LFPR	−0.0208	0.0194	−1.08	0.300
Estimated short-run coefficients				

Note. The symbols ; , and represent statistical significance at 1, 5, and 10% levels, respectively. Source: own computation (2024).

Table 2 presents the estimates of both the long- and short-run coefficients of the ARDL model. The analysis shows that precipitation positively and significantly influences cereal crop production in both the long and short run, while temperature has a negative and significant impact on cereal crop output in the long run. The results also indicate that arable land, fertilizer application, and CO2 emissions positively and significantly affect cereal crop production in the long run. In the short run, labor force participation has a positive, whereas fertilizer application has a negative and significant impact on cereal crop output in Zimbabwe during the study period.

The estimated model confirms that precipitation has a positive and significant impact on cereal crop production in both the long and short run. This is likely because agriculture in Zimbabwe is primarily rain-fed with limited irrigation. A 1% increase in precipitation results in a 0.16% increase in cereal crop production in the long run and a 0.87% increase in the short run, all else being equal. This finding aligns with the research by Li et al. (2021), which reported a positive impact of precipitation on bean farming in China. Additionally, a 1% increase in temperature leads to a 1.12% decrease in cereal crop production, reflecting the substantial moisture requirements of cereal crops. This negative effect of temperature is consistent with Pindiriri (2022), who noted that high-temperature stress adversely affects agricultural production.

In the long run, the coefficient for arable land shows a positive and significant effect on cereal crop production, with a 1% increase in arable land area resulting in a 1.62% increase in production. This finding suggests that cereal crop output is highly responsive to changes in cultivated area, consistent with studies by Pawlak & Kołodziejczak (2020) and Mushore et al. (2021). Moreover, the model's long-run estimates reveal that CO_2 emissions have a positive and statistically significant effect on cereal crop production, with a 1% increase in emissions leading to a 0.23% increase in production. This supports the findings of Ahsan et al. (2023) in Pakistan and Abbas Ali et al. (2020) in India, who also reported a positive impact of CO_2 emissions on cereal crop production.

Fertilizer consumption has a positive and statistically significant impact on cereal crop production in the long run at a 1% significance level, implying that a 1% increase in fertilizer use per arable land leads to a 0.34% increase in production. This result is consistent with studies by Ketema (2021) and Chandio et al. (2023). However, in the short run, the estimated lag of fertilizer has a negative and significant impact on cereal crop production at a 5% significance level. This could be due to the initial fertility of cultivated lands and the potential harmful effects of excessive fertilizer application, such as nutrient runoff leading to algal blooms.

Labor force participation has a positive and significant effect on cereal crop production at a 5% significance level in the short run, reflecting the labor-intensive nature of agriculture in Zimbabwe. A 1% increase in labor force participation in agriculture results in a 0.45% increase in cereal crop production. This finding is consistent with the research by Musafiri and Mirzabaev (2019), who reported positive effects of labor force on agricultural production. The negative and significant coefficient of the estimated error correction term (ECT) indicates the presence of cointegration among the variables and suggests that 112% of the short-run disequilibrium is adjusted towards long-run equilibrium within a year, indicating a good adjustment speed.

4.4. Diagnostic Tests.

Table 4: Diagnostic test of the ARDL model.

Diagnostic tests	Chi^2/F-statistics	$P > \|t\|$
Serial correlation	0.189	0.6635
Normality	0.56	0.7542
Functional form	0.30	0.8245
Heteroscedasticity	29.00	0.4125

Source: own computation (2024).

After analyzing the ARDL model, the study conducted several diagnostic tests, including the Breusch-Godfrey LM test (for Serial Correlation), Ramsey RESET (for Model Specification or Omitted Variables), Jarque-Bera (for Normality), and Breusch–Pagan–Godfrey test (for Heteroscedasticity). The results, presented in Table 4, indicate that the Breusch-Godfrey LM test confirms there is no serial autocorrelation in the model. The Jarque-Bera test demonstrates that the error term in the model is normally distributed. Furthermore, the Ramsey RESET and Breusch–Pagan–Godfrey tests show that the ARDL model is correctly specified and free from heteroscedasticity issues.

5. Conclusion and Policy Implications

This study analyzed the long-term effects of climate change on cereal crop production in Zimbabwe using 42 years of time series data. The research employed the Autoregressive Distributed Lag (ARDL) model. The bounds test and the estimated coefficient of the Error Correction Term (ECT) indicated cointegration among cereal crop production, precipitation, temperature, labor force participation rate, fertilizer consumption, carbon dioxide emissions, and arable land. The model's results showed that precipitation positively influences cereal crop production both in the short and long term, while temperature negatively affects it in the long term. Additionally, fertilizer consumption, arable land, and carbon dioxide emissions positively impact cereal crop production in the long term, whereas the labor force participation rate has a positive effect in the short term. The positive and significant effect of the labor force participation rate highlights the labor-intensive nature of cereal crop production in Zimbabwe. However, fertilizer consumption was found to have a negative and significant short-term impact. The ECT coefficient suggests that 112% of the disequilibrium error is corrected annually towards equilibrium. The findings of this research could be beneficial for policymakers and scholars.

Based on the findings from a study on the effects of climate change on cereal crop production, several key policy recommendations emerge. Policymakers should prioritize investment in research and development of climate-resilient crop varieties, focusing on genetic improvements for drought, heat, and pest resistance. It is essential to enhance infrastructure for efficient water management, including the promotion of water-saving irrigation techniques and the construction of reservoirs. Supporting sustainable agricultural practices through incentives for farmers to adopt conservation tillage, crop rotation, and agroforestry can mitigate adverse impacts. Establishing early warning systems and providing timely weather forecasts can help farmers make informed decisions. Additionally, policies should encourage diversification of crops to reduce reliance on a few staple cereals. International cooperation and knowledge sharing on best practices and technological innovations will be critical. Finally, integrating climate change adaptation strategies into national agricultural policies and providing financial support to smallholder farmers will be vital for building a resilient agricultural sector.

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