The Impact of Climate-Smart Agriculture and CO2 Emissions on Food Security in Asian Developing Countries (2000-2023)

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Abstract
Asian developing countries face the challenge of food security. This persists under the pressure of rapid population growth, environmental degradation, and climate change that not only affect economic growth but also their agricultural systems. The paper examines the nature of the interconnection between the climate-smart agriculture (CSA), food security, and carbon dioxide (CO_2) emissions within the context of Asian developing countries from 2000 to 2023. Using fixed-effects models with strong standard errors, interaction analysis and Dumitrescu-Hurlin causality tests; it is found that the negative effects of CO_2 emissions on food security are highly significant, not just in terms of reduced productivity but also in terms of long-term environmental externalities. CSA on the other hand will directly alleviate these adverse impacts as it will promote resource-use efficiency, climatic stress-resilience, and development in agricultural sectors that are sustainable. Policy implications emphasize the importance of the scaled adaptation of CSA, original integration of agricultural, climate, and trade strategies, and the need to invest in sustainable food systems to ensure zero hunger, climate action and sustainable production.
Keywords: Climate Smart Agriculture, Carbon dioxide, Food Security

1. Introduction

The Asian developing states are amid a severe national problem on a global scale. The necessity to secure food supply to a growing population during the growing threat of climate change. The area, which hosts more than half of the global population already deals with serious food insecurity issues, hundreds

of millions of people are hungry or cannot get access to healthy and adequate food regularly. International community defines food security as the fact that, people at all times can access adequate, safe and nutritious food that satisfy their dieting needs, socially, economically and physically (Declaration, 1996). This is a global imperative that is greatly targeted at the Asian continent which hosts about 60% of the world population. A large number of this population is in rural regions and is still very vulnerable to climate change effects (Yadav & Lal, 2018). As the population of the continent is projected to exceed 5.2 billion by 2050, the issue of sufficient food production is destined to be even more severe (Rao et al., 2019).

The challenge is further enhanced by the high population growth and urbanization, which subject the food production systems to constantly growing pressure. Meanwhile, the region is especially vulnerable to the impacts of a changing climate, including warming temperatures, inconsistent precipitation distribution, and high occurrence rates alongside intensification of extreme weather events, including drought and floods(Saira et al., 2023; Mehdi et al., 2025). Such climatic changes pose a direct threat to the agricultural productivity, and the effects of global warming may reduce the future crop yields by 10 to 50 percent before the end of the century (Habib-ur-Rahman et al., 2022; Batool et al., 2025).This subsequent interference in agricultural systems endangers all four pillars of food security availability, access, stability and utilization. One of the major causes of this climate crisis is the rise in the atmospheric concentration of greenhouse gases (GHGs), and carbon dioxide (CO_2). Ironically, the problem of climate change has affected the agricultural sector in Asia, yet it is one of the major causes of climate change. In 2020, the region contributed 42% of the global agri- food CO_2 equivalent emissions, with rice production, use of fertilizer and livestock rearing being the main contributors (Rashami et al., 2025). This forms a complicated feedback mechanism in which the attempts to generate more food, in their turn, lead to the same climate changes that threaten food security in the long term.

In response to this multifaceted crisis, Climate-Smart Agriculture (CSA) has come to be recognized as an essential strategic approach. CSA can be described as a type of approach that can convert and reorient agricultural systems and meet three simultaneous goals: (1) boosting agricultural output and incomes in a sustainable manner; (2) adapting and gaining resilience to climatic conditions; and (3) reducing or eliminating GHG emissions where feasible (FAO). The implementation of CSA practices can thus be described as a critical channel through which the smallholder farmers can adapt to the climate change impacts, enhance their food security, and ensure that they

achieve the Sustainable Development Goals objectives (Teklu et al., 2024). CSA is imperative as one of the primary strategies that can lessen the impact of climate-related changes and empower communities to tackle the pressing development challenge of global food and nutrition security (Owino et al., 2022; Wakweya, 2023; Naeem et al., 2025). Through the CSA, reduction of negative cycle between agriculture and climate change can be achieved by encouraging practices like precision agriculture, better water management, stress-resistant types of crops and agroforestry, which in turn leads to development of productive and sustainable food systems (Hussain et al., 2021; Ali et al., 2025; Tan & Lee, 2025).

Despite the growing recognition of CSA's potential, a notable research gap remains. Although the negative effects of climate change on agriculture are widely documented, there is still limited macro-level empirical work that directly measures how rising CO_2 emissions influence the various dimensions of food security in Asian developing countries. In addition, strong quantitative evidence on the extent to which CSA practices can mitigate the impacts of CO_2 emissions at a regional level is largely absent. This study seeks to fill this important gap by offering a comprehensive empirical assessment of the relationships among CO_2 emissions, Climate-Smart Agriculture, and food security. Through this analysis, the research aims to provide policymakers with practical, evidence-based insights that can support the development of resilient, sustainable, and food-secure futures across the region.

2. Literature Review

Climate change is well known to be one of the serious threats to world agriculture. The effects of high temperatures on crop yields, the heightened rate of extreme weather experiences, pose a major threat to food security and the lives of millions of people directly (Waris et al., 2023). The agricultural sector's reliance on stable climate patterns makes it particularly vulnerable (Vaghefi et al., 2016), with climate-induced shocks such as droughts and floods directly impacting food supplies (Kogan et al., 2019; Longston et al., 2025). Climate change effects cut across the four pillars of food security. Reduced crop yields threaten availability, with forecasts for South Asia and Africa predicting severe losses in staple commodities such as maize and wheat by 2050 (Knox et al., 2012). Weather-related production volatility undermines stability, and access is jeopardized as reduced supply and greater risk lead to higher food prices, reducing the purchasing power of the poor (Edoja et al., 2016; Field, 2012; Ali et al., 2025; Rizwan & Iqbal, 2025).

In this context, the particular role of carbon dioxide is a more complex and controversial image. As much as CO_2 is the cause of the unfavorable climatic changes, literature also covers its direct and at times conflicting

impact. On the one hand, this high CO_2 in the atmosphere has a direct negative impact on the utilization pillar of food security through the reduced nutritional quality of staple crops. Most of the researches have verified that crops produced under high CO_2 levels have reduced concentrations of key nutrients such as protein, iron and zinc, a silent menace to the health of the human being (Teressa, 2021; Weyant et al., 2018; Zhu et al., 2018; Arshad et al., 2025; Ali et al., 2025; Hou & Yuan, 2025).

Conversely, there is also evidence of the so-called carbon fertilization effect, according to which a rise in CO_2 levels can trigger photosynthesis and raise the biomass of plants (Kimball, 2016). This phenomenon has been credited with the satellite data proving the global process of greening of vegetation (Zhu et al., 2016). This has drawn disputable conclusions in the regional studies. Indicatively, a study in Pakistan concluded that the increase in temperature, associated with the rise in CO_2 emissions, had a positive effect on wheat production both in the short-term and long-term (Janjua et al., 2014; Ali & Audi, 2016), and a study in Tunisia also found that increase in annual temperatures negatively affected the productivity of cereals and a study in Tunisia also found that increase in annual temperatures negatively affected the productivity of cereals (Ben Jebli & Ben Youssef, 2017; Ali et al., 2021; Marc et al., 2025). This tension of the negative climate and food effects versus possible biomass benefits is one of the main issues that have not been resolved yet.

To make this situation even more complex, there is the ironic aspect that agriculture is also a major contributor to GHG emissions. Research in Tunisia to Pakistan has found agricultural activity, especially fertilization and livestock production to be one of the key long-term contributors to CO_2 emissions(Owusu & Asumadu-Sarkodie, 2017; Waheed et al., 2018; Audi et al., 2025). This creates a vicious cycle where the effort to produce more food contributes to the very climate change that threatens long-term food security. To address these interrelated issues, Climate-Smart Agriculture (CSA) has developed into a prominent model to revolutionize the agricultural systems. According to the FAO (2010), Climate-smart agricu=lture (CSA) is designed to tackle climate change and food security by enhancing production, resilience, reduction in GHG emissions, and national development objectives (Ewbank, 2019; Marc et al., 2025). The approach is considered essential to the poorest farmers in the world, as they rely on agriculture as their source of livelihood (GCEC, 2014). The literature reports numerous CSA practices, such as Conservation Agriculture to increase soil health (Legoupil et al., 2014), improved water management practices to increase water-use efficiency (Chowdhury & Bajracharya, 2018; Marc et al., 2025; Carlo, 2025), the

implementation of varieties of crops resistant to climate change, and Precision Agriculture to make the best use of inputs (Gomiero, 2019). CSA enhances the value chain players and smallholder farmers through promoting climate resilience crops and farming practices. The development of more resilient agricultural systems to climate change is also impossible without improving the health of soils (Zaman et al., 2021; Martin, 2025). The reduction of greenhouse gas emissions is one of the most significant elements of Climate Smart Agriculture, which can reduce the negative environmental impact of the agricultural activities (Ma & Rahut, 2024; Ahmed & Hu, 2025).

One of the key concerns is that, although the potential of CSA is recognized, its implementation is fraught with tremendous barriers. The literature states that CSA practices are extremely place-specific and need to be adjusted to local agro-ecological and socioeconomic contexts (Thornton et al., 2018). A combination of socio-economic constraints is a major barrier to adoption especially among the smallholder farmers which are the giant in the Asian agricultural scene. The geographic composition of the country, the absence of adaptive infrastructure, and overdependence on climate-sensitive agriculture are the primary factors that contribute to the great extent of climate change vulnerability in the country (Kishore et al., 2021; Chowdhury & Hassan, 2025). They consist of poor access to credit and other financial facilities, poor quality land tenure, limited access to agricultural extension services to transfer technical education, and more extensive market failures (Imran et al., 2018; Lee & Zhuang, 2025). Therefore, although the body of literature on CSA in Asia is expanding, it is still said to be in its infancy, and more data is still in need to make the contribution to the adaptive capacity of farmers.

The current literature proves that the connection between CO2 emissions, agricultural activities, and food security is not simple and remains unsolved. The literature includes contradictory evidence on the net effect of CO2, and at the same time suggests CSA as another essential solution with large-scale effectiveness yet to be proved empirically. This review demonstrates that there are two important research gaps that this study intends to fill in. To begin with, although numerous studies have focused on the one-way influence of carbon emissions on food security, they did not come to a conclusion (Affoh et al., 2022; Bary & Hakim, 2025), which is why, there is a significant gap in the literature on macro-level, empirical research that measures the net effect of increased CO2 emissions within the various economies of developing Asia. Second, despite the popularity of CSA to increase resilience and reduce emissions (Zaman et al., 2021; Martin &

Camerone, 2025), no quantitative research evaluates if the practice of CSA can moderate this multifaceted relationship at a regional or national scale.

Thus, the research will make its contribution to the literature through panel data analysis to present important empirical results on the two aspects of this dual role of CO2 emissions. It will also explore how much Climate-Smart Agriculture can alleviate this association and provide a clue to construct more resilient and sustainable food systems in the Asian developing nations.

3. Data and Methodology

3.1. Data Sources and Analysis

In the study, the secondary data source is based on the World Development Indicators (WDI) and Climate Engine, using annual data of 14 Asian countries between the year 2000 and 2023. The study utilizes annual panel data to examine the relationships among macroeconomic and climate-related variables. The data set encompasses macroeconomic indicators and environmental variables relevant to the study objectives.

Table 1: Variables Description and Data Sources

Variables	Symbols	Descriptions	Unit	Source
Dependent Variable				
Food Production index	FPI	Food production index refers to food crops, which are edible.	Index (base year=100)	WDI
Independent Variables				
CO2 Emissions (Total, excl. LULUCF)	CO2	Carbon dioxide (CO_2) emissions total, excluding land use, land-use change, and forestry (LULUCF).	Metric tons (Mt CO_2)	WDI
Energy use	EU	Use of primary energy before transformation into other end use fuels.	kg/capita oil equivalent	WDI
Annual Average Mean Surface Air Temperature	TEM	Annual average of near-surface air temperature, representing the mean climate conditions across each year for each region or country	°C (Celsius)	Climate engine
Trade (% of GDP)	TRD	Total exports and imports of goods and services divided by gross domestic product.	% of GDP	WDI

Population Growth (Annual %)	PG	The rate at which the population grows per annum calculated as the difference between birth rates and the death rates plus the net migration.	%	WDI
Renewable Internal Freshwater Resources per Capita	REW	Total volume of internal renewable water resources (surface and groundwater) divided by the total population.	Cubic meters per capita	WDI
Water Productivity, Total	WP	GDP per cubic meter of freshwater withdrawal. Measures economic output generated from water use.	Constant 2015 US$ GDP/m³	WDI
Forest Area (% of Land Area)	FR	Proportion of land area that is classified as forest, according to FAO definitions.	%	WDI
Fertilizer Consumption	FC	Measured as the amount of plant nutrients used per unit of arable land, including nitrogen (N), phosphate (P₂O₅), and potash (K₂O).	kg per hectare of arable land	WDI

3.2. Model Specification

3.2.1. Regression Model

The fundamental empirical model employed to examine the relationship between food security and factors that determine the relationship is given as follows:

$$FPI_{it} = \alpha + \beta_1 CO2_{it} + \beta_2 CSA_{it} + \beta_3(CO2 \times CSA) + \beta_4 EU_{it} + \beta_5 TEM_{it} + \beta_6 TRD_{it} + \beta_7 PG_{it} + \mu_{it}$$

$$lnFPI_{it} = \alpha + \beta_1 lnCO2_{it} + \beta_2 CSA_{it} + \beta_3(lnCO2 \times CSA) + \beta_4 lnEU_{it} + \beta_5 lnTEM_{it} + \beta_6 lnTRD_{it} + \beta_7 lnPG_{it} + \mu_{it}$$

Where:

$lnFPI_{it}$ = log of the Food Production Index for country i at time t (dependent variable).

$lnCO2_{it}$ = log of Carbon Dioxide Emissions for country i at time t.

CSA_{it} = Climate Smart Agriculture Index for country i at time t (as an index, it is not log-transformed)

$lnEU_{it}$ = log of Energy Use for country i at time t.

$lnTEM_{it}$ = log of Annual Average Mean Surface Air Temperature for country i at time t.

$lnTRD_{it}$ = log of Population Growth for country i at time t.

$lnPG_{it}$ = log of Trade for country i at time t.

β_0 = Intercept term.

$\beta_1 \ldots \ldots \beta_0$ = Coefficients measuring the direct effect or elasticity of the respective independent variables on the Food Production Index.

This log-log model of most of the variables (except CSA) permits the interpretation of coefficients as elasticities, or as percent change in FPI due to a 1 percent change in the independent variable.

3.3. Climate Smart Agriculture Index (CSA) Construction

To build the Climate Smart Agriculture Index (CSA) the Principal Component Analysis (PCA) is used. PCA refers to a multivariate statistical methodology applied in minimizing the dimensionality of a dataset without necessarily losing most of the variability. It includes the elimination of multiple possibly correlated variables to a smaller set of variables that are uncorrelated referred to as principal components.The process makes sure that the variables are equally scaled.

In this analysis, the CSA index is created to take measures of the effective level of climate-smart agriculture in the developing countries of Asia. PCA is used to integrate the following variables in the index:

Total Water Productivity (WP)

Renewable Internal Freshwater Resources per Capita (REW)

Forest Area (% of Land Area) (FR)

Fertilizer Consumption (FC)

The resulting CSA index is then incorporated into the core regression model as a direct explanatory variable.

3.4. Interaction Term Specification

To investigate the effect of a certain independent variable on food security that may depend on the level of a different variable. An extended version of the core model is added with an interaction term. Two independent variables, X1 and X2 are then usually added to a multiple regression model:

$$Y_{it} = \alpha + \beta 1 X_{1,it} + \beta 2 X_{2,it} + \beta_3 X_{1,it} X_{2,it} + \mu_{it},$$

Where:

$X_{1,it}$ And $X_{2,it}$ are two independent variables of interest

$(X_{1,it} X_{2,it})$ represents their interaction term.

The type of interaction that is chosen should rely on the specific nature of the concepts to be analyzed and not on the specific measure of variables to use in the statistical analysis (Andersson et al., 2019). The interaction term was developed through mean-centring since there were possible multicollinearity effects between the interaction term and its constituent variables.

$$\ln\_CO2\_CSA\_inter\_c = (\ln\_CO2 - \overline{\ln\_CO2}) \times (CSA - \overline{CSA})$$

This is done to reduce the possibility of multicollinearity among the interaction term and its constituent variables, and this approach improves the interpretation of main effects and estimates of standard errors that are unbiased (West et al., 1996). The choice of the variables to interact with will be informed with the theoretical suggestions about the mutual effects on food security.

4. Methodology

4.1. Unit Root Test

When using Panel data, it is important to ensure that the statistical properties of the variables are checked. Level panel data are not very likely to be non-stationary and regressions performed on non-stationary data usually lead to spurious conclusions. The unit root test applied in this study is the Levin, Lin and Chu (LLC) test (Levin et al., 2002). This test is applicable to balanced panels, and in this case, the assumption is that a similar unit root process applies across cross-sectional units, but each unit has its own fixed effects and time trends. The basic model for the LLC test is:

$$y_{i,t} = \rho y_{i,t-1} + \mu_0 + \delta_t + \mu_i + \gamma_t + \varepsilon_{i,t,} \qquad i=1,2,.....,N; \quad t=1,2,.....,T$$

Here, μ_0 and γ_t are individual and time-specific effects respectively, while δ_t reflects the time trend. First, the error term $\varepsilon_{i,t}$ is thought to be independently and identically distributed, $IID(0, \sigma^{2)})$ although the authors permit a serial correlation by introducing lagged first differences -like Augmented Dickey-Fuller (ADF) test. The LLC test statistics have the same asymptotic properties with sufficient lags increasing with the sample size. With the assistance of Levin-Lin-Chu test, the stationarity of individual panal series is verified

The null hypothesis of Levin Lin Chu Test (LLC) for stationery is as follows;

$H0 : \rho = 0 \ (Series \ is \ non \ stationary)$

$H0 : \rho \neq 0 \ (Series \ is \ stationary$

Levin A., et al (2002) notes that Levin-Lin-Chu test of stationarity is effective when T(time-periods) is 5 to 250 and the cross-section units N is 10-250. The reason behind LLC test of stationarity selection is based on the fact that we are dealing with 14 cross-sectional units, 24 time periods in our analysis (Arowolo & Ekum, 2016).

4.2. The Fixed Effect Model

One of the methods used to capture some of the effects of a panel data model is the fixed effects (FE) regression. This FE approach is based on the assumption that the effects are quite fixed parameters which can be estimated. There are many such econometric challenges that are likely to be experienced:

i) There can be a correlation of unobserved specific fixed effects and the regressors used

ii) The regressors can be related even in case of the presence of disturbance term that affects the dependent variable.

iii)   It can lead to simultaneity biases due to endogenous nature of some of the regressors.

The fixed effects model takes into consideration unobserved, time-invariant individual-specific factors that could affect the dependent variable and can be correlated with the independent variables. It also assumes that these effects are constant parameters which are country specific and estimable. The model has a country-specific intercept error (μ_i). These estimators that can be used to estimate the fixed effects model are the Within Group (WG) estimator, First Difference (FD) estimator or Least Squares Dummy Variable (LSDV) estimator.

4.3. Fixed Effect Hypothesis Testing (F-Test)

F-test is used to ascertain whether fixed effects model offers a significantly superior fit in comparison with pooled OLS model. The comparison of the R-squared of the two models is as follows:

$$F_{group\ effects} = \frac{(R^2_{FE} - R^2_{pooled})/(N-1)}{(1-R^2_{FE})/(NT-N-k)}$$

Where:

R^2_{FE} = R-squared from the fixed effects model

R^2_{pooled} = R-squared from the pooled OLS model

N = No. of countries

T = No of time periods

k = No. of regressors (excluding the intercept)

The null hypothesis (H0: μ1 = μ2 = …. = μn= 0) is that no significant fixed effects (favoring pooled OLS). The alternative hypothesis (H1: μ1≠μ2≠ …. ≠μn= 0) indicates that the level of fixed effects is significant. The rejection of the null hypothesis is statistically significant F-statistic, and it shows that the country-specific fixed effects and favoring the fixed effects model.

4.4. Hausman Test

A significant diagnostic tool used to compare the fixed and random effects models and identify the most appropriate model to use in the specified panel data is Hausman test. It tests the uniformity of the random effects estimator.

The development of the test is found on the following: The fixed effects estimator is consistent at the null hypothesis and alternative hypotheses. Random effects estimator is efficient when the null hypothesis is true and inconsistent when the null hypothesis is false. According to the null hypothesis (H0), the unobserved individual effects (vi) are non-correlated to the regressors (x). This implies that the random effects model is more efficient and consistent. The alternative hypothesis (H1) states that the unobserved individual effects are correlated with the regressors, meaning the fixed effects model is the appropriate choice, as the random effects estimator would be inconsistent. The test statistics are distributed as chi-square. The null hypothesis will be rejected to indicate that fixed effects are favored.

4.5. Granger Causality Test

The Granger hypothesis to examine the causality of the relationship between the variables of Climate-Smart Agriculture (CSA) and Food Security and CO2 emissions is to be used. Following the ground breaking contribution of Granger (1969), a variable x is Granger-caused by a variable y, when the past values of x contain some information that is useful in the predictability of y on top of the information that is available with the past values of y.

The panel Granger causality test of Dumitrescu and Hurlin (2012) is the method applied in this study in the assessment of the influence of causal relationships among countries to explain the possibility of heterogeneity of causal influences that would arise in countries. This approach will allow us to distinguish between countries with and without causality, and it is therefore highly appropriate to heterogeneous panel data.

$$Y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma i, k y i, t - k + \sum_{k=1}^{K} \beta i, k x i, t - k + \varepsilon_{i,t} \qquad (6)$$

The null hypothesis:

$H_0: \boldsymbol{\beta_{i,k} = 0}$ For all (no granger causality from x to y)

The alternative hypothesis:

$H_0: \boldsymbol{\beta_{i,k} \neq 0}$ For at least some i

The null hypothesis assumes that there will be no Granger causality between x and y in all the panel units. The null is rejected implying that historical values of x can give valuable information which will be used to predict the value of y, i.e., a Granger-causal relationship exists. The test is best applicable to our data consisting of 14 countries in 24 years period, where the heterogeneity is assumed in the dynamics of causation. We examine the direction of causality between

- CO2 and Food Security
- Food Security and Climate Smart Agriculture
- CO2 and Climate Smart Agriculture

4.6. Diagnostic Test

The following Diagnostic tests are applied to check Autocorrelation, Heteroscedasticity, Multicollinearity, and Cross-sectional dependency.

Panel data models can also induce autocorrelation of idiosyncratic errors, which can break the classical OLS assumptions and result in estimation inefficiency and biased statistical inferences. First-order autocorrelation is checked with the help of the Wooldridge autocorrelation test. The reason why this test is specifically useful is its ease of use, as well as its capability to apply to unbalanced panels and short-term series. The VIF test is used to check serial correlation of the error term particularly when estimating a fixed effects model, by estimating a first differences model and testing lagged residuals as significant predictors of differenced residuals (Wooldridge, 2002).

Hypotheses:

H_0: No Autocorrelation (errors are independent).

H_1: Autocorrelation exists (errors are correlated)

Walled test is a test for detecting heteroscedasticity in a regression model. The Modified Wald test for GroupWise heteroskedasticity (Pesaran-type) was conducted following the fixed effects estimation.

4.7. Hypotheses

H_0: Homoscedasticity (constant variance of residuals).

H_0 : Heteroscedasticity (variance of residuals depends on the level of an independent variable)

The VIF test is used to check serial correlation of the error term particularly when estimating a fixed effects model, by estimating a first differences model and testing lagged residuals as significant predictors of differenced residuals.

To ensure the presence of cross sectional dependence in the panel data.we applied two major tests which are Breusch Pagan LM (Breusch S., 1980) and Pesaran CD (Pesaran, 2004) on the basis of panel structure. The Lagrange Multiplier theory is used to create the BreuschPagan LM-Test which is used in small N, large T panel. LM statistic is obtained as

$$LM = T \sum_{i=1}^{N-1} p \sum_{j=i+1}^{N} p_{ij}^2$$

p_{ij}^2 where represents the estimated of the pairwise correlation coefficient of the residual between cross-sectional units i and j. This statistic obeys the chi-square (N(N-1)/2)/2 degrees of freedom with the null hypothesis being the null cross-sectional dependence in the asymptotic. However, the impact of the Large-sample test or LM test is that N is large, and T is not infinite and hence the test cannot be well-centered in such cases. In the presence of small and

typical values of N and T, Pesaran (2004) then suggested a Cross-sectional Dependence (CD) test which is also resistant among the factors of heterogeneity and non-stationary (Belsley et al., 2005).

The CD statistic is computed as

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} p \sum_{j=i+1}^{N} p_{ij}^2$$

In the case of unbalanced panels, Pesaran (2004) developed a slightly modified version, which corrects concerning diverse length of observations across units. The adjusted CD statistic has Tij as a consideration in the determination. Among the cross-sectional units, these tests are critical in the diagnosis of whether the standard panel estimators are valid or whether they ought to use cross-sectional dependence-adjusted estimators (e.g., Driscoll-Kraay, xtdcce2**).**

5. Result and Discussion

The empirical findings of how CO2 emission and agricultural climate-smart (CSA) practices affect food security in developing countries in Asia. The main econometric model is used a fixed effects panel regression model which has Driscoll-Kraay robust standard errors of heteroskedasticity and cross-sectional dependence. It also examine an interaction effect between CSA and CO2 emissions. Well to justify robustness, panel unit root (Levin-Lin-Chu) tests, large scale diagnostic tests (autocorrelation, heteroskedasticity, cross-sectional dependence) and the Hausman test were also reported to justifiable model selection.

Levin-Lin-Chu (LLC) panel unit root tests performed to test the stationarity of the variables. Table 2 reveals that most of the variables such as lnfpi, lnco2, lneu, lntem, lntrd, lnpg and co2csainter_c remain at the regular significance levels (I (0)). There was a borderline stationarity in the csa variable (p-value = 0.06). Since most of the variables (including the dependent one) are I (0), the Fixed Effects model is still suitable at describing the short-to-medium run dynamics, despite the possibility of a mixed order of integration of some variables.

Table 2: *Unit Root Test*

Variables	Levin-Lin-Chu P- value at level I (0)
ln_fpi	0.0107
ln_co2	0.0004
Csa	0.06*
co2_csa_inter_c	0.037
ln_eu	0.0008

ln_tem	0.000
ln_trd	0.002
ln_pg	0.003

The main econometric findings of the Fixed Effects (FE) panel regression that uses Driscoll-Kraay robust standard errors. The Hausman test justified the use of the FE model and showed that there was a significant correlation between the country-specific effects that were not observed and the regressors. The R-squared in the model is 0.614, which implies that 61.4 percent of within country variation in lnfpi is captured by the independent variables.

Table 3: Fixed Effects

ln_fpi	Coef.	St.Err.	t-value	p-value	95% Conf	Interval]	Sig
ln_co2	.317	.031	10.10	0	.255	.379	***
Csa	.2	.037	5.48	0	.128	.272	***
co2_csa_inter_c	-.035	.011	-3.24	.001	-.056	-.014	***
ln_eu	-.165	.058	-2.84	.005	-.279	-.051	***
ln_tem	-.083	.153	-0.54	.586	-.385	.218	
ln_trd	-.114	.027	-4.14	0	-.168	-.06	***
ln_pg1	.049	.027	1.85	.066	-.003	.102	*
Constant	4.653	.529	8.79	0	3.612	5.694	***
Mean dependent var	4.523		SD dependent var	0.142			
R-squared	0.614		Number of obs	336			
F-test	71.533		Prob > F	0.000			
Akaike crit. (AIC)	-702.857		Bayesian crit. (BIC)	-672.321			

A 1% change in CO_2 emissions has a statistically significant impact on FPI of 0.317%. This is a short-term positive effect that can be explained by the fact that CO_2 fertilized crops enhanced crop yield, especially with C3 crops. In developing Asia, the increased CO_2 emissions usually accompany the improved agriculture mechanization and industry that temporarily improve food production and availability at the cost of long-term environment degradation. Csa one unit is correlated with a 0.2 percent increase in FPI. This goes a long way to prove the efficacy of CSA practices (e.g., water productivity, efficient nutrient use, forest area) in increasing food availability and climate shock-resilience in a sustainable manner, in line with the principles of FAO and empirical research of other studies. Ln_eu(Coefficient = -0.165, $p < 0.005$) 1 percent change in energy use is linked to a -0.165 percent change in FPI. High energy demand may substitute for agricultural resources, and an increase in energy prices may adversely affect the input utilization of farmers, resulting in low food production, particularly where the inefficient energy

systems are present in developing countries. ln_tem (Coefficient = -0.083, p = 0.586): The impact of average temperature on FPI is negative, but statistically non-significant in the short run. This implies that the effect of short-run changes in temperatures on food production might not directly or strongly be felt because of adaptive measures (e.g., irrigation, drought-resistant crops), or the lagging nature of the effects. ln_trd (Coefficient = -0.114, p < 0.001): An increase in trade openness by 1% is related to a reduction in FPI by 0.114%. This is a short term and adverse correlation that could be owed to rise in imports of food in place of local production, allocation of resources to export crops and exposure of the developing economies to the global food price shocks. lnpg (Coefficient = 0.049, p = 0.066) 1% growth in the population will lead to a 0.049% growth in the FPI (significant at 10%). Population growth in the short term may raise the agricultural labor supply and spur demand driven agricultural intensification, and hence greater food production but this observation must be interpreted with caution as the confidence interval runs over zero. co2_csa_inter_c (Coefficient = -0.035, p = 0.001) This significant negative interaction term is a major result. It is showing that the short-term beneficial effect of CO2 emissions on food security is basically mitigated when CSA practices are adopted at a higher rate. It points to the fact that there is critical buffering effect. Through more adoption and implementation of the practice of Climate-Smart Agriculture practices (CSA), the beneficial effect of the levels of CO2 emissions (lnco2) to Food Security (lnfpi) is quite elevated or dampened. This will be the most basic way in which CSA can help to counter the positive influence of CO2 emission that is not sustainable. The specified finding is aligned with the theoretical background of Climate-Smart Agriculture and the adaptation and mitigation pillars, in particular.

It does not just end with the hypothesis statements but provides empirical evidence of the fact that csa is not only a direct promoter of food security. It actively contributes to the alteration of the relationship between the agents of climate (like co2) and food production. The interplay in this case is apparently complicated because csa can be best applied to offset the impact of co2 by suggesting it to be more important than the mere additive outcome. This will be abundantly interpreted in terms of how adaptations in agriculture can combine with adaptations in the environment to produce patterns that are more sustainable. The large negative coefficient of the co2-csa interaction term (-0.035, p = 0.001) confirms that csa is not only a productivity booster, but also a strategic buffer that neutralizes the short-term co2 fertilization effect. It is also making the food system less vulnerable to the harmful effects caused by greenhouse gas emissions. This highlights the fact that csa is the

entry point of how agriculture can be guided towards resilience and sustainability.

Dumitrescu-Hurlin (D-H) Panel Causality Test was used to test the causal relationships of the key variables in the panel. The causes were determined using the Test which established the direction of causality between lnfpi,lnco2 and csa.

Table 4: *Granger Causality Test Results*

Test direction	Lag	Z_bar	p-value
ln_co2→ln_fpi	2	4.38	0.00
ln_fpi→ln_co2	1	3.57	0.00
csa→ln_fpi	1	4..20	0.00
ln_co2 → csa	2	4.16	0.00
csa → ln_co2	2	-0.4783	0.632

lnco2-lnfpi (Bidirectional Causality): A strong evidence of a bidirectional causal relationship exists between lnco2 granger-causes lnfpi (p=0.000, Lag 2) and lnfpi granger-causes lnco2 (p=0.000, Lag 1). It means that there is a complicated feedback process, in which emissions can be said to Granger-cause food production, and agricultural activities, conversely, can be said to Granger-cause emissions. lnfpi - csa (Unidirectional Causality): csa Granger-cause lnfpi (p=0.000, Lag 1). This affirms that CSA practices are a causal factor of enhanced food security results. lnco2 - csa (Bidirectional Causality with Lag) lnco2 unidirectionally Granger-causes csa (p=0.000, Lag 2), which indicates that increasing CO2 levels is a motivating factor in CSA adoption. On the other hand, csa is not a Granger-cause of lnco2 in the short run (p=0.632, Lag 2) but in the long run (p=0.000, Lag 6). This shows that though CO2 leads to the adoption of CSA, the mitigation ability of CSA in the reduction of CO2 emissions is experienced in the long run.

Diagnostic tests to be applied in testing Hausman test, Autocorrelation, Heteroscedasticity and Cross-sectional dependency are as follows. Hausman test is a test which compares Fixed Effects (FE) model and Random Effects (RE) model. This can be attributed to the fact that, the p-value is less than 0.05 to reject null hypothesis on whether the RE estimator is consistent. It establishes that Fixed Effects is the appropriate model specification since it controls unobserved heterogeneity across nations. The null hypothesis is that the first order autocorrelation is non-existent. The fact that p-value is more than 0.05 does not reject the null. It would imply that there is no serially correlated and time autocorrelated panel residuals. H 0: The panel is homoscedastic (similar variances). We do not accept the null hypothesis as the p-value is less than 0.05, which therefore means that we accept the null

hypothesis to be false. Pesaran test is applied to test the relationship between cross-sectional units (i.e. countries). The null hypothesis is the independence of cross-sections. The large p-value (smaller than 0.05) shows that there are residuals by cross-country, which do not fulfill the typical assumptions of FE. That is the reason that it is justified to use Driscoll-Kraay standard errors that is both resistant to cross-sectional dependence and heteroskedasticity.

Table 5: Diagnostic test

Tests	Chi-squared P-value	P-value	
Hausman test	331.74	0.000	Fixed Effects preferred
Autocorrelation (Wooldridge test)	1.523	0.239	No evidence of serial correlation ($p > 0.05$)
Heteroscedasticity (Walled test)	907.3	0.000	Heteroskedasticity, Cross-sectional
cross sectional independence(Pesaran's test)	5.335	0.000	dependence is present (Use Driscoll-Kraay standard errors to correct)

6. Conclusions

The paper critically examined the complex interplay between CO_2 emissions, Climate-Smart Agriculture (CSA), and the food security of 14 developing countries in Asia in a 24-year study. Through the use of sound panel econometric procedures, which comprise Fixed Effects regression and Dumitrescu-Hurlin panel Granger causality, we were in a position to make empirical contributions to the climate-food security nexus and the CSA mitigating potential. Fixed Effects regression analysis revealed that CO_2 emissions had a positive direct effect on Food Production Index (FPI), which was statistically significant. Although this observation appears to be counterintuitive given the climate change issues, this observation might be an indication of a carbon fertilization effect, with increased atmospheric CO_2 potentially increasing the rate of photosynthesis and hence the crop production of particular plant species under certain environmental conditions. The Dumitrescu Hurlin Granger causality tests however revealed that there is a two way causality between CO_2 emission and food security. It reflects that CO_2 emissions can not only affect food security, but also that different changes in food security, possibly caused by land use changes, energy use

patterns, or agricultural processes, can also cause changes in the level of emissions. More importantly, CSA recorded a statistically significant and significantly positive direct impact on food security, which validates its theoretical potential in supporting agricultural productivity, sustainability, and resilience. The interaction between CO_2 and CSA was observed to be negative and significant, and the implication is that the CSA is a successful mitigating factor against the positive impact of CO_2 emission on food security. This means that in areas where CSA has been very active, the agricultural systems will not be very dependent on the CO_2-induced yield improvement, hence improving their sustainability and resilience in future. This observation closely conforms to adaptive capacity theories and resilience theory, making CSA an important environmental risk buffer. Additional Granger causality analysis showed that CSA is Granger-caused by CO_2 emissions, implying that rising environmental pressure can be a decisive factor in the introduction of a nation to climate-resilient agricultural strategies. Interestingly, Granger-cause effect of CSA was also observed to reduce CO_2 emissions after longer lags (six periods) which also lends empirical support to the fact that CSA can mitigate the effects in the long-term. This confirms the idea of climate adaptation and justifies the critical role of CSA in the attainment of the goals of environmental sustainability, as identified by the IPCC (2022).

In addition to the fundamental relations, our analysis also demonstrated that the energy consumption and openness to trade were negatively correlated with food security, and this fact may indicate the inefficiency and structural susceptibility of the current agricultural systems. On the other hand, increasing population was positively related to food production, probably because of the higher demand and supply of labor force. Curiously, the effect of temperature on it was not significant in a linear form with a p-value, and it shows that further studies on climatic variables require more subtle and context-dependent analyses.

To sum up, this study assumes that climate change is not a situational determinant, but it is an underlying determinant in 21st century agriculture. The results of our study provide solid empirical data that the CSA is not only a reactive reaction but a change agent that has quite impressive effects that go beyond direct food production to include other larger sustainability, resilience, and climate change mitigation concerns.

6.1.   Recommendation

Based on the obtained empirical results, we suggest the following strategic measures to bring about food security and climate resilience in developing Asian countries. Make large-scale investments in digital technologies, precision agriculture technologies (e.g. sensor-based irrigation, drone

monitoring), and AI-based decision support systems. But to make sure that these technologies do not contribute to the inequality gap, these investments should be accompanied by extensive climate education and specific communication programs. Local governments should use the local community institutions, including village councils and agricultural extension centers, to provide geographically specific climate information. With a primary emphasis on enhancing the level of policy awareness among the smallholder farmers, the states can enhance the level of adoption of climate-resilient varieties of crops and precision tools, as the technological progress will be based on the real needs and perceptions of the local farming community. Introduce policies and incentives to farmers to use on-farm renewable energy sources and energy efficient agricultural equipment. Re-consider trade policies to focus on domestic food production and enhance local/regional food value chains and eliminate dependence on unstable global markets. Invest in water efficient irrigation, rainwater harvesting and restoration of natural water bodies. Achieve the development of modern storage systems, cold chain and transportation networks to reduce food loss. Invest in flood defenses involves better drainages and updated weather surveillance systems that can give early alerts to the rural population.

Integrate the principles of CSA into the national food security policies and match them with Nationally Determined Contributions (NDCs) to mitigate the agricultural sector. Engage in active implementation of international climate finance mechanisms (e.g. Green Climate Fund) to implement CSA and develop infrastructure. Renew and increase funding and technical assistance to CSA programs, based on effective programs that have shown real results on green agriculture, resilience, and climate smart practices throughout the region. These suggestions reiterate the need to have a knowledge-based and holistic transformation of agricultural systems being fueled by innovation, strategic investment, and integrated policy frameworks.

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