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CLIMATE DYNAMICS AND AGRICULTURAL SECTOR PERFORMANCE IN INDONESIA: A PROVINCIAL PANEL DATA ANALYSIS

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Abstract

This study examines the effect of climate dynamics on agricultural sector performance in Indonesia using province-level panel data for the period 2014–2023. Employing panel regression estimations under several specifications, the analysis investigates whether average temperature and rainy-day frequency, as the main climate-related variables, are associated with real agricultural Gross Regional Domestic Product (GRDP), which captures the market value in the food and horticultural crop subsectors. The empirical results indicate that temperature is the most robust climate-related predictor of agricultural GRDP across model specifications. By contrast, the effect of rainy-day frequency is more sensitive to the inclusion of year fixed effects, suggesting that rainfall-related effects may be influenced by common annual shocks or broader time-specific conditions. Population is generally positively associated with real agricultural GRDP, although its magnitude weakens after accounting for year effects. Overall, the Driscoll–Kraay estimations confirm that temperature remains a consistent predictor of agricultural GRDP, while the estimated effects of rainy days, land cover, and population are more dependent on model specification, particularly the treatment of year fixed effects.

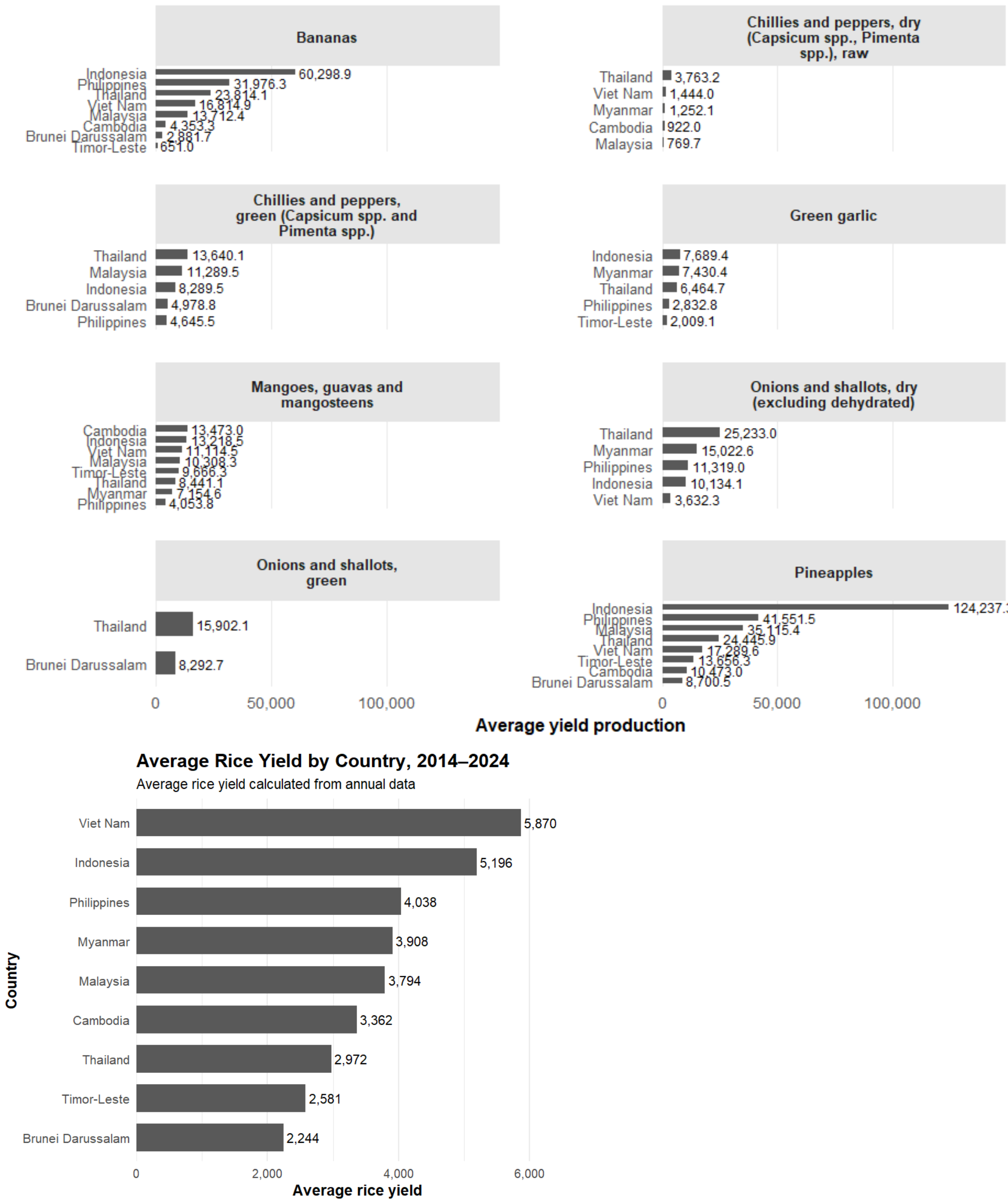
Keywords: Climate, Temperature, Rain Frequency, Agriculture Sector, GRDP

INTRODUCTION

The agricultural sector remains a strategic priority in Indonesia's efforts to strengthen food security and achieve greater food self-sufficiency. A key agenda highlighted in the National Medium-Term Development Plan (*Rencana Pembangunan Jangka Menengah Nasional*, RPJMN) 2025–2029 is the improvement of agricultural land productivity as part of broader efforts to sustain economic resilience and long-term development. In this regard, the Government of Indonesia targets agricultural GDP growth of 3.46% by the end of 2029. However, climate change has emerged as a critical risk that may undermine these efforts by increasing uncertainty in agricultural production systems and posing significant challenges to productivity enhancement.

Data from the Food and Agriculture Organization (FAO) indicate Indonesia's important role in food and horticultural crop production, particularly within Southeast Asia. On average, during the period 2014–2024, Indonesia ranked second after Viet Nam in rice yield, with an average harvest yield of 5,196 kg/ha, compared with 5,870 kg/ha in Viet Nam. Indonesia also recorded a dominant position in several horticultural commodities in ASEAN, including banana production, with an average yield of 60,298 kg/ha, garlic, with an average yield of 7,689 kg/ha, mango, with an average yield of 13,218 kg/ha, and pineapple, where Indonesia also showed a strong regional position (see Figure 1).

Meanwhile, World Bank data show that Indonesia's average surface air temperature increased from 25.87°C in 1990 to 26.16°C in 2023. Average rainfall also fluctuated over time but showed an increasing tendency, rising from 2,595 mm in 2014 to 2,997 mm in 2024. These patterns suggest that Indonesia's agricultural sector operates within a changing climatic environment, making it increasingly important to examine how climate variability may affect agricultural sector especially focusing on food and holticulture crops within regions in Indonesia.



Source: https://www.fao.org/faostat/en/#data/QCL (graph is generated by the authors)

Figure 1. Average Yield Production (in kg/ha during period 2014-2024) for Selected Food and Holticulture Crops, by item and ASEAN Countries.

This study examines the effect of climate variability on agricultural sector performance in Indonesia, with particular emphasis on the food and horticultural subsectors, by exploiting province-level variation over the last decade. It contributes to the existing literature by providing recent subnational empirical evidence on the climate–agriculture nexus in Indonesia. This contribution is particularly important because previous studies in the Indonesian context remain limited in terms of recent data coverage and have not consistently employed robust econometric procedures to address potential issues commonly associated with panel data estimation, such as unobserved heterogeneity, heteroskedasticity, serial correlation, and cross-sectional dependence. The remainder of this paper is organized as follows. Section 2 reviews relevant empirical studies, to provide a conceptual and empirical basis. Section 3 describes the data sources, variable construction, and estimation strategy used to identify the association between climate indicators and agricultural GRDP. Section 4 presents and discusses the descriptive statistics and regression results. Finally, Section 5 concludes the study.

LITERATURE REVIEW

Climate change has become a major concern in agricultural and natural-resource economics because of its direct implications for agricultural productivity, food security, rural livelihoods, and regional economic development. Temperature and rainfall are commonly used indicators of climate dynamics, yet their effects on agriculture are rarely uniform across regions, crops, and time horizons. At the global level, Ortiz-Bobea et al. (2021) show that anthropogenic climate change has slowed agricultural total factor productivity growth since 1961, with the strongest adverse effects observed in warmer regions such as Africa, Latin America, and the Caribbean. Similarly, Olper et al. (2021) find that climate variation in Italy has limited average effects on GDP per capita but substantial negative effects on agricultural productivity, particularly under persistent temperature increases.

Comparative evidence from developing regions also confirms the vulnerability of agriculture to climate shocks. Saleem & Smirnova (2026) find that rising temperature negatively affects agricultural production per capita across South Asia, Southern Africa, and South America, while precipitation also has direct negative effects on production consistent across different specifications (Panel Corrected Standard Errors (PCSE), Feasible Generalised Least Square (FGLS), and Driscoll-Kraay estimates). Chamma (2025) using Sub-Saharan Africa shows that rising temperatures negatively affect GDP percapita, while higher average monthly annual precipitation is positively associated with GDP per capita, with agriculture being more climate-sensitive than industry, manufacturing, and services.

Evidence from Africa, South Asia and the wider Asian region shows that rainfall, temperature, and seasonal climate variability may produce different effects. For example, Asfew & Bedemo (2022) in Ethiopia, find precipitation positively affects cereal production in both the short and long run, Benkachchach & El Issaoui (2024), in Morocco, also find that rainfall is positively associated with agricultural GDP. Singh et al. (2017), using fixed-effects panel data for Gujarat State, India, find that rainfall generally supports crop yields, whereas higher temperature tends to reduce them. Lee et al. (2012), using panel data for 13 Asian countries, show that higher summer temperature and rainfall may increase agricultural production, while higher fall temperature reduces production in Southeast Asia.

Other Asian studies similarly reveal mixed effects. Jatuporn & Takeuchi (2023) find that rainfall and water-related factors support agricultural performance. Tran et al. (2025) show that rainfall is a major predictor of crop output productivity in Vietnam. Joseph et al. (2023) show that continued temperature increases may reduce global rice production, whereas rainfall directly affects rice output through both drought and flood-related risks. Rahman et al. (2017) also demonstrate that rainfed rice in Bangladesh is vulnerable to frequent dry and wet periods, with productivity responses varying across ecosystems.

Souvannasouk et al. (2021), focusing on ASEAN countries during 1995–2018, further show that climate-induced changes in temperature and precipitation affect agricultural GDP. Precipitation and average temperature effects show mixed results across different estimator, negative magnitude was found when using panel least square specification, but becomes positive when using FGLS. Sangkhaphan & Shu (2019), using provincial panel data for Thailand from 1995 to 2015 also show that rainfall negatively affects annual economic growth unevenly across regions and sectors, both estimated using FGLS or OLS.

Compared with the broader international literature, empirical investigation from Indonesia remains relatively limited. Febriandika & Rahayu (2021), using provincial panel data for 2016–2018, find that agricultural land area is positively associated with GDP, while temperature, rainfall, and air quality index do not show significant partial effects. At the household level, Asih (2020) provides more specific evidence from Central Sulawesi, showing that rainfall and temperature variability negatively affect household food security, particularly food availability and stability. Bintariningtyas et al. (2025) find that land area, precipitation, and air pressure significantly affect rice productivity in East Nusa Tenggara, while temperature is not statistically significant.

These findings suggest that Indonesian evidence remains fragmented across different outcomes, including GDP, household food security, and rice productivity, while relatively limited attention has been given to broader agricultural sector performance at the subnational level. Moreover, the mixed findings across previous studies indicate that climate effects may depend on data period, empirical specification, commodity composition, and the outcome variable used. Therefore, further empirical research is needed to examine how temperature, rainy-day frequency, and environmental conditions influence agricultural GRDP across Indonesian provinces, particularly in a tropical archipelagic setting where agricultural systems are highly diverse and climate exposure varies substantially across regions.

METHOD

The data used in this study are obtained from the Environmental Statistics Reports for the period 2014–2023, which supply information on climatic and environmental indicators, including average temperature, rainy-day frequency, rainfall, and the land-cover index across Indonesian provinces. The dependent variable is real GRDP in the agricultural sector consisting of food crops and holticulture crops, sourced from Indonesia's Statistic Agency (*Badan Pusat Statistik*, BPS). The dataset covers 32 provinces in Indonesia. DKI Jakarta is excluded because it functions primarily as the national capital and has a relatively limited agricultural sector. North Kalimantan Province is also excluded due to data limitations for several variables.

The empirical strategy adopts a panel data approach as also used by Chamma (2025), Febriandika & Rahayu (2021), Saleem & Smirnova (2026), Sangkhaphan & Shu (2019), Singh et al. (2017), Souvannasouk et al. (2021). The dataset comprises 32 provinces observed over a 10-year period. As an initial step, this study estimates baseline panel regression models using both the Fixed Effects (FE) and Random Effects (RE) estimators, as specified in the following equations:

For FE:

$$l\_GRDP\_agric_{it} = \alpha + \beta_1 temp_{it} + \beta_2 l_{-rainyday_{it}} + \beta_3 landcover_{it} + \beta_4 l\_pop_{it} \quad + \mu_i + \varepsilon_{it} \;\ldots(1)$$

While for RE:

$$l\_GRDP\_agric_{it} = \alpha + \beta_1 temp_{it} + \beta_2 l_{rainyday_{it}} + \beta_3 landcover_{it} + \beta_4 l\_pop_{it} \quad + \delta_i + \varepsilon_{it} \;\ldots\; (2)$$

In equation (1), we control μ_i as the unit fixed effect, which here is province, assuming that it may be correlated with the regressors. In equation (2), random unit-specific effect is represented by δ_i, and we assume uncorrelated with the explanatory variables. Hausman Test according to p-value is then used to choose FE or RE. If p-value < 0.05, we reject the null-hypothesis saying random effects is consistent and efficient. For robustness check, we also estimate panel data incorporating for year dummies. Equation (3) below assumes if fixed effect is choosen:

$$l\_GRDP\_agric_{it} = \alpha_i + \lambda_t + \mathrm{X}'_{it}\beta + \varepsilon_{it}, \qquad i = 1, \ldots, N; t = 1, \ldots, T \qquad (3)$$

Where $l\_GRDP\_agric_{it}$ denotes the dependent variable for province i in year t, α_i represents province fixed effects, λ_t represents year fixed effects, ε_{it} is the idiosyncratic error term, and X'_{it} is a vector of explanatory variables (see Table 1 for list of regressors compiled) with β stands for the vector of estimated coefficients. Clustered standard error is also applied at the province level, and the variance-covariance matrix is written as follows:

$$\widehat{Var_{clust}}(\hat{\beta}) = (\tilde{\mathrm{X}}'\tilde{\mathrm{X}})^{-1}\left[\sum_{i=1}^{N} \tilde{\mathrm{X}}'_i\, \hat{\varepsilon}_i \hat{\varepsilon}'_i \tilde{\mathrm{X}}_i\right](\tilde{\mathrm{X}}'\tilde{\mathrm{X}})^{-1} \qquad (4)$$

Where $\tilde{\mathrm{X}}$ denotes the transformed regressors after removing fixed effects and year effects, and $\hat{\varepsilon}_i$ denotes the vector of residuals for province *i*. Finally, we also address issues of cross-sectional dependence using Pesaran test, and apply Driscoll-Kraay (D-K) Standard Errors approach that is robust to heteroskedasticity, serial correlation, and cross-sectional dependence across provinces (Hoechle, 2007). The corresponding variance-covariance matrix is written generally as below:

$$\widehat{Var_{DK}}(\hat{\beta}) = (\tilde{\mathrm{X}}'\tilde{\mathrm{X}})^{-1}\hat{S}_{DK}(\tilde{\mathrm{X}}'\tilde{\mathrm{X}})^{-1} \qquad (5)$$

All regression analyses were conducted using Stata program. Cross-sectional dependence was examined using the Pesaran test implemented through the "xtcsd" command, while D-K estimator uses "xtscc" command (Hoechle (2007)). Given that the time dimension of the panel is relatively short than with the cross-sectional dimension, the Panel-Corrected Standard Errors (PCSE) estimator was not adopted because it is less appropriate for this panel structure. In addition, since several related studies employ FGLS, this study also estimates FGLS specifications as a sensitivity check and compares the results with the D-K estimates, although these additional results are not reported in the main text for brevity.

Table 1. Definition of Variables

No	Label of Variable	Definition	Source of Data
1	l_GRDP_agric	Real Gross Regional Domestic Product (GRDP) for Agriculture Sector (food crops and holticulture) (in log)	BPS
2	$temp$	Temperature (in degree celcius)	Environmental Statistic Report
3	$l_{\_rainyday}$	Rainy-day frequency (in log)	Environmental Statistic Report
4	$landcover_{it}$	Index of land cover	Environmental Statistic Report
5	l_pop_{it}	Number of population (in log)	Environmental Statistic Report

Source: the authors

RESULTS AND DISCUSSION

This section presents the results with clear descriptions. Results can be supplemented with tables, graphs (pictures), and/or charts. The discussion section describes the results of processing data or information, interpreting the findings logically, linking them to relevant reference sources, and the implications of the findings. [Times New Roman, 12, normal].

Table 2 shows the descriptive statistics of the variables used in the empirical analysis. Agricultural GRDP records considerable variation across the panel, with an average value of IDR 13,962.27 billion and a relatively large standard deviation of IDR 19,390.34 billion. The wide range between the minimum value of IDR 260 billion and the maximum value of IDR 78,073 billion indicates substantial heterogeneity in the scale of agricultural economic activity across observational units. After transformation into natural logarithmic form, agricultural real GRDP has a mean of 8.78 and a standard deviation of 1.29, indicating that the log transformation helps reduce the scale effect and compress extreme variation.

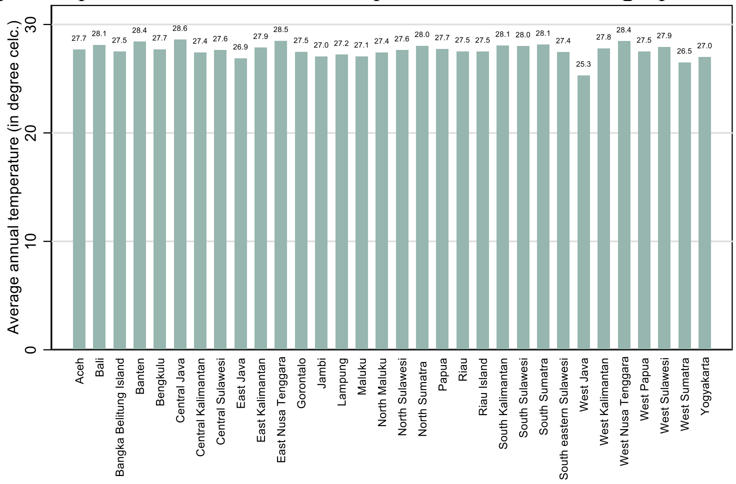
The climate variables also show meaningful variation across the sample. Temperature has an average value of 27.60°C, with a standard deviation of 1.02°C and a range from 23.3°C to 32.6°C. Although the standard deviation is relatively modest, the range suggests that the observed regions experience different thermal conditions that may affect agricultural productivity through crop stress, evapotranspiration, and growing-season suitability. Rainy days record an average of 122.71 days, with a standard deviation of 60.81 days, indicating substantial variation in rainfall frequency across regions and years. The minimum and maximum values, ranging from 38 to 304 days, further suggest that the sample contains areas with very different rainfall regimes. The logged rainy-day variable has a mean of 4.70 and a standard deviation of 0.44, reflecting a more compact distribution after logarithmic transformation.

Table 2. Descriptive Statistic of Variable Used in the Analysis

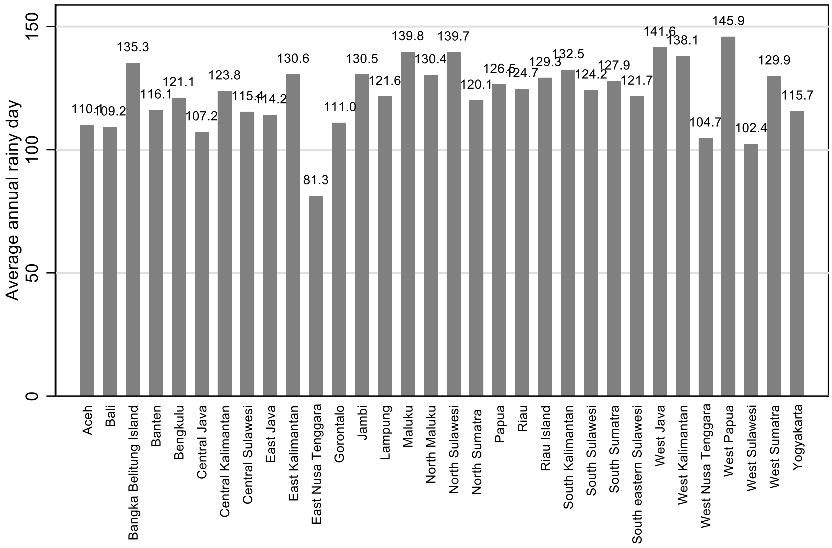
Variable	unit	Obs	Mean	Std. dev.	Min	Max
GRDP_agriculture	billion IDR	320	13962.27	19390.34	260	78073
l_GRDP_agriculture	natural logarithm	320	8.780326	1.29444	5.560682	11.2654
temperature	celcius degree	319	27.59865	1.02035	23.3	32.6
rainy_day	frequency	317	122.7135	60.80592	38	304
l_rainyday	natural logarithm	317	4.704043	0.4432295	3.637586	5.717028
landcover index	index	320	60.26875	16.69189	29.66	100
population	Thousand	320	7934.215	11270.01	850	50345.2
l_population	natural logarithm	320	8.401995	0.9760651	6.745236	10.82666

Source: the Authors

The land-cover index has an average value of 60.27, ranging from 29.66 to 100, with a standard deviation of 16.69. This reflects differences in vegetation quality, land-use intensity, environmental conditions, or the extent of land resources relevant to agricultural activity. Population also displays substantial heterogeneity, with a mean of 7,934.22 and a standard deviation of 11,270.01 (in thousand). The large gap between the minimum value of 850 and the maximum value of 50,345.2 (in thousand) indicates that the sample includes both relatively small and highly populated regions. The log form provides a more stable representation of demographic scale.



Source: the Authors
Figure 2. Average annual temperature across provinces



Source: the Authors
Figure 3. Average annual rainy day across provinces

Figure 2 presents the annual average temperature across 32 provinces in Indonesia. On average during 2014-2023, several provinces, including Central Java, East Nusa Tenggara, and Banten, experienced relatively high temperatures, whereas West Java and West Sumatra recorded comparatively lower temperatures during the same period. Figure 3 illustrates the average annual frequency of rainy days across the 32 provinces over the ten-year period. The highest rainy-day frequencies, ranging from approximately 139 to 145 days per year, were observed in West Papua, West Java, and Maluku, while East Nusa Tenggara, Central Java, and West Sumatra recorded the lowest frequencies, ranging from around 81.3 to 96.5 days per year. Moreover, Figure 4 indicates a substantial decline in the national average frequency of rainy days between 2014 and 2023. For example, the average number of rainy days dropped from approximately 203 days in 2017 to only 80.3 days in 2023, suggesting a marked shift in rainfall occurrence across Indonesia during the study period.

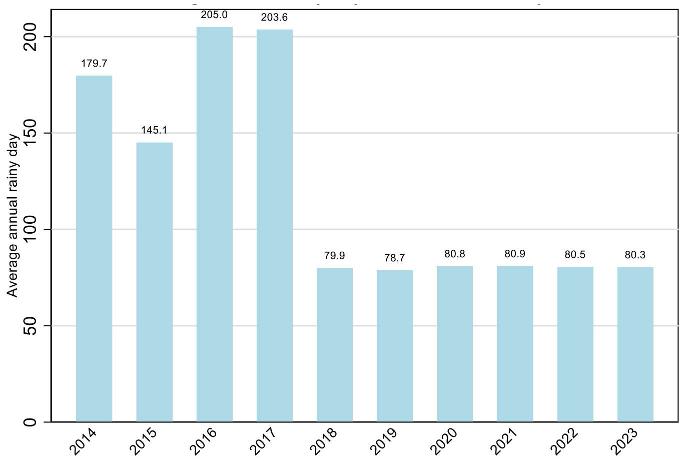


Figure 4. Average annual rainy day across year

Table 3 presents the conventional panel regression results providing FE and RE results with agricultural GRDP expressed in natural logarithmic form as dependent variable. The temperature coefficient is positive, statistically significant at the 1% level in both models. In the FE specification, a one-degree Celsius increase in temperature is associated with an approximately 1.82% increase in agricultural GRDP, *ceteris paribus*. The RE estimate is nearly identical, at 1.83%, suggesting that the positive association between temperature and agricultural GRDP is relatively stable across the two model structures. This result, however, does not necessarily imply that higher temperature is universally beneficial for agriculture, but may reflect the specific agro-climatic conditions, crop composition, regional production systems, or short-run within-region temperature variation observed in the sample.

Table 3. Panel data regression results comparing FE and RE estimator

Dependent Variable: Agriculture GRDP (in log)		
VARIABLES	**(1) FE**	**(2) RE**
temp	0.0182***	0.0183***
	(0.0043)	(0.0047)
l_rainyday	-0.0648***	-0.0574***
	(0.0090)	(0.0096)
landcover	0.0007	0.0004
	(0.0005)	(0.0006)
l_pop	0.2464***	0.3972***
	(0.0520)	(0.0511)
Constant	6.4596***	5.1869***
	(0.4731)	(0.4877)
Observations	316	316
R-squared		
Within	0.4088	0.3953
Between	0.7670	0.7658
Overall	0.7435	0.7543
Hausman Test (Prob > chi2)	0.000	
Number of ID	32	32

The coefficient of logged rainy days is negative and statistically significant at the 1% level in both models. The FE estimate indicates that a 1% increase in rainy days is associated with an approximately 0.065% decrease in agricultural GRDP, while the RE model suggests a slightly smaller effect of around 0.057%. This negative relationship implies that a higher frequency of rainy days may not always support agricultural output. In practical terms, excessive rainfall frequency would mean disruption in agricultural activities through waterlogging, flooding, delayed planting or harvesting, reduced sunlight exposure, higher pest and disease incidence, and limited access to production areas. Thus, the result suggests that the distribution and intensity of rainfall may be more important than rainfall occurrence alone.

The land-cover index has a positive but statistically insignificant coefficient in both the FE and RE models. The insignificance of this variable may reflect limited within-region variation in land cover over the study period, or the possibility that land-cover quality affects agricultural output indirectly through other channels. By contrast, population is positively and significantly associated with agricultural GRDP in both models. In the FE model, a 1% increase in population is associated with an approximately 0.246% increase in agricultural GRDP, while the RE model produces a larger elasticity of 0.397%. This positive effect may capture the role of population as a proxy for labour availability, local demand, market size, and broader regional economic scale.

Table 4. Panel data regression results comparing FE method using cluster with and without year fixed effects, and FE D-K method

Dependent Variable: Agriculture GRDP (in log)				
	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	**FE_cluster**	**FE_cluster+year**	**FE_DK**	**FE_DK+year**
temp	0.0182***	0.0093**	0.0182**	0.0093***
	(0.0037)	(0.0044)	(0.0058)	(0.0018)
l_rainyday	-0.0648***	0.0381	-0.0648**	0.0381*
	(0.0078)	(0.0460)	(0.0255)	(0.0194)
landcover	0.0007	0.0005	0.0007**	0.0005
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
l_pop	0.2464*	0.0740	0.2464*	0.0740*
	(0.1272)	(0.0476)	(0.1277)	(0.0346)
Constant	6.4596***	7.5632***	6.4596***	7.5632***
	(1.0622)	(0.5198)	(1.2260)	(0.3777)
Year Fixed Effect	NO	YES	NO	YES
Observations	316	316	316	316
R-squared				
Within	0.4088	0.6152	0.4088	0.6152
Between	0.7670	0.7422		
Overall	0.7435	0.4648		
Prob > F	0.0000	0.0000	0.0000	0.0000
Pesaran's Test (Pr)	0.0000	0.0617		
Number of ID	32	32		
Number of groups			32	32

Note: FE_Cluster refers to the fixed-effects model estimated with clustered standard errors; FE_Cluster + Year refers to the fixed-effects model estimated with clustered standard errors and year fixed effects; FE_DK refers to the fixed-effects model estimated with D-K standard errors; and FE_DK + Year refers to the fixed-effects model estimated with D-K standard errors and year fixed effects.

Finally, Table 3 informs the Hausman test which reports a probability value of 0.000, strongly rejecting the null hypothesis that the RE estimator is consistent. Therefore, the FE model is statistically preferred. The FE model explains approximately 40.88% of within-region variation in agricultural GRDP, while the relatively high between and overall R-squared values indicate that cross-regional differences also account for a substantial share of agricultural GRDP variation.

Moving to Table 4, the result reports a set of robustness estimations based on the fixed-effect framework, with combination of clustered standard errors, year dummy variables, and Driscoll–Kraay (D-K) standard errors. We also test using FGLS estimator our model and find consistent results in coefficient or significance. However, due to our N is relatively larger than T, and we find that Cross-Sectional Dependence exists (see columns (1) and (2) in Table 4) according to Pesaran's, as suggested by Hoechle (2007), we prefer to select D-K estimator.

The temperature variable remains positive and statistically significant across all specifications (see Table 4 columns (1) through (4)), indicating a robust association between temperature and agricultural GRDP. In the FE model with clustered standard errors, the coefficient of temperature is 0.0182 and significant at the 1% level, suggesting that a one-degree Celsius increase in temperature is associated with an approximately 1.82% increase in agricultural GRDP, ceteris paribus. The same coefficient is obtained under the Driscoll–Kraay specification without year dummies, although statistical significance declines slightly to the 5% level. When year dummies are introduced, the coefficient decreases to 0.0093 but remains statistically significant in both the clustered and Driscoll–Kraay models. This reduction implies that part of the temperature effect in the baseline specification may be related to common annual shocks. Nevertheless, the persistence of a positive and significant coefficient after controlling for year effects suggests that temperature maintains an independent within-region association with agricultural GRDP during the study period.

The effect of rainy days is more sensitive to model specification. In the specifications without year dummies (column (1)), logged rainy days have a negative and statistically significant coefficient. The coefficient of -0.0648 implies that a 1% increase in rainy days is associated with an approximately 0.065% decrease in agricultural GRDP. However, after year dummies are included, the coefficient changes sign and becomes positive, although it is statistically insignificant in the clustered specification and only weakly significant in the Driscoll–Kraay specification. This change indicates that the estimated relationship between rainy days and agricultural GRDP is strongly influenced by common year-specific shocks. Therefore, the rainy-day coefficient should be interpreted cautiously, as its direction and statistical strength are not fully stable across specifications.

The land-cover index shows limited and less consistent evidence of association with agricultural GRDP. In the clustered specifications, the coefficient is positive but statistically insignificant. Under the Driscoll–Kraay specification without year fixed effect (column (3)), however, the coefficient becomes statistically significant at the 5% level, although its magnitude remains very small.

Finally, population covariate remains positively associated with agricultural GRDP, but its statistical significance and magnitude also vary across specifications. In the FE-cluster model without year dummies, the coefficient of logged population is 0.2464 and significant only at the 10% level, implying that a 1% increase in population is associated with an approximately 0.246% increase in agricultural GRDP. When year dummies are included, the coefficient declines substantially to 0.0740. It becomes statistically insignificant in the clustered specification but remains weakly significant in the Driscoll–Kraay specification. This decline suggests that part of the population effect may overlap with broader time trends, such as demographic expansion, or changes in aggregate demand. Nevertheless, the positive sign is consistent with the interpretation that population may capture labour availability, local market size, and the scale of regional economic activity.

The inclusion of year dummies substantially improves the explanatory power of the model. The within R-squared increases from 0.4088 in the baseline fixed-effect specification to 0.6152 when year dummies are included, indicating common time-specific factors explain a considerable share of within-region variation in agricultural GRDP. All specifications are jointly significant, as shown by Prob > F = 0.0000, confirming that the included explanatory variables collectively contribute to explaining agricultural GRDP variation.

Overall, the results indicate that temperature is the most robust climate-related predictor in the model, while the effect of rainy days depends strongly on whether common annual shocks are controlled. Population generally shows a positive association with agricultural GRDP, although its effect weakens after accounting for year effects. Taken together, the results suggest that agricultural economic performance is shaped by climatic and demographic factors, but the estimated effects are sensitive to the way unobserved time shocks and panel-dependence structures are addressed.

The statistical evidence as shown in Table 3 and 4 broadly supports the central argument in the literature that the relationship between climate dynamics and agricultural performance is heterogeneous, context-specific, and sensitive to empirical specification. In particular, the large variation in agricultural GRDP and climate indicators supports the need for subnational panel analysis, as aggregate national-level estimates may conceal important spatial heterogeneity, as suggested by Bintariningtyas et al. (2025), Jatuporn & Takeuchi (2023), Lee et al. (2012), Tran et al., (2025).

The fixed-effect results show that temperature has a positive and statistically significant association with agricultural GRDP. This finding suprisingly contrasts with much of the global and Global South literature, including Ortiz-Bobea et al. (2021), Olper et al. (2021), Saleem and Smirnova (2026), and Chamma (2025), which generally find that rising temperature reduces agricultural productivity or economic performance. However, the result is not entirely inconsistent with the literature because Lee et al. (2012) show that some seasonal temperature increases may support agricultural production in certain Asian contexts. The positive temperature coefficient may reflect the specific regional, crop-mix, and short-run climatic conditions captured by the data, or the fact that agricultural GRDP measures economic value added rather than physical crop yield or total factor productivity.

The negative coefficient of rainy days in Table 3 provides stronger support for the literature emphasizing the adverse effects of rain variability. The finding is consistent with Saleem & Smirnova (2026), Chamma (2025), Joseph et al. (2023), Souvannasouk et al. (2021), Tran et al. (2025), though contrasts with studies conducted by Jatuporn & Takeuchi (2023), Singh et al. (2017), Asfew & Bedemo (2022), and Benkachchach & El Issaoui (2024). The result suggests that the more frequent rainy days may indicate excessive rainfall, flooding, delayed harvesting, increased pest and disease pressure, or disruption of farming activities.

Table 4 strengthens the interpretation by showing how the results change under alternative fixed-effect specifications using clustered standard errors, year dummies, and D-K standard errors. Temperature remains positive and statistically significant across all specifications, although its coefficient declines from 0.0182 to 0.0093 after year dummies are included. This suggests that part of the temperature effect in the baseline model may be associated with common time-specific shocks, such as national agricultural policy, macroeconomic conditions, commodity prices, or annual climate patterns. Nevertheless, the persistence of statistical significance under both clustered and Driscoll–Kraay standard errors indicates that temperature remains a robust predictor of agricultural GRDP within the sample. This finding partly contrasts with the dominant literature on the negative consequences of warming, but it also reinforces the literature's broader message that climate impacts are not uniform and may differ depending on the outcome variable, temporal scale, agricultural subsector, and regional context.

CONCLUSION

The empirical findings indicate that agricultural GRDP is systematically associated with climatic and demographic factors, although the strength and direction of these relationships vary across model specifications. The Hausman test confirms that the fixed-effect estimator is preferred over the random-effect model. The robustness estimations refine these conclusions. Temperature remains positive and statistically significant under clustered standard errors, D-K standard errors, and models with year dummies, although its coefficient becomes smaller after controlling for common annual shocks.

By contrast, the effect of rainy-day frequency is less stable across specifications. It is negative and statistically significant in models without year fixed effects, but becomes positive and either weakly significant or statistically insignificant once year effects are included. This instability suggests that rainfall-related effects are highly sensitive to the treatment of common time-specific shocks and should therefore be interpreted with caution.

To conclude, the results support the argument that climate conditions are relevant to agricultural economic performance, while also confirming that the climate–agriculture relationship is context-specific and model-dependent. This study acknowledges several limitations. First, the dependent variable is measured at the macroeconomic level, which may not fully capture commodity-specific productivity responses to climate variability. Second, the relatively short time dimension of the panel limits the application of more dynamic panel-data approaches. Future research should therefore extend the observation period, possibly to 20–25 years, and examine specific agricultural commodities or yield-based indicators to better identify the mechanisms through which climate variability affects agricultural productivity.

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