Research Paper

Extreme weather impact and urban–rural income gap: a study on the mitigation effect of agricultural insurance

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ABSTRACT

Climate change-induced extreme weather events are increasingly recognised as a structural driver of widening economic inequality between urban and rural populations. This study investigates the causal relationship between extreme weather shocks, agricultural insurance penetration, and the urban–rural income gap using a panel dataset of 30 provincial-level administrative units across two emerging economies over 2000–2023. A Two-Way Fixed Effects (TWFE) regression framework, complemented by Instrumental Variable (IV) two-stage least-squares estimation and Difference-in-Differences (DID) identification, is employed. Results show that a one-standard-deviation increase in extreme weather frequency elevates the urban–rural income gap ratio by 0.471 points ($p < 0.001$). Agricultural insurance penetration exerts a significant moderating effect: each 10-percentage-point increase in coverage mitigates approximately 28.3% of the weather-induced income gap widening. Mediation analysis reveals that primary transmission channels include agricultural output loss (standardised path coefficient = 0.41), farm household income reduction (0.38), and induced rural-to-urban labour migration (0.22). Heterogeneity analysis across provincial income terciles confirms that the insurance mitigation effect is most pronounced among low-income rural provinces ($\beta = -0.38$), indicating a progressive risk-pooling function of agricultural insurance. Findings are robust across Propensity Score Matching (PSM), event study analyses, and alternative extreme weather operationalisations. Results provide empirically grounded policy guidance for subsidised agricultural insurance programmes as targeted inequality reduction instruments under accelerating climate change.

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1. INTRODUCTION

Increased intensity of extreme weather events such as flooding, droughts, tropical cyclones and longer heatwaves is one of the upcoming most critical economic pressures of the twenty first century. The Intergovernmental Panel on Climate Change (IPCC) has forecast that they will increase significantly in both number and intensity in the future across all representative concentration pathways (RCPs) [1]. It is important to question the relationship between structural inequality of incomes and the unequal exposure for rural agricultural communities when considering the interaction of shocks and structural inequality.

Income disparities between urban and rural areas are a longstanding issue in the Global South, caused by unequal productivity of sectors, access to financial resources and level of social protection coverage [2]. Agricultural households are highly dependent on precipitation and temperature sensitive activities, and are very vulnerable to weather extremes which can wipe out productive activity over many months in just a few days. Countries with more diversified occupational structures, and with better institutional insulation, have more weather-resistant economies, particularly in cities [3]. Extreme weather events thus could be systemic structural drivers of expanding pre-existing economic inequities.

Agricultural insurance has become a popular tool for transferring risks faced by the rural household sector, that face weather related income volatility [4]. In the last two decades, index-based crop insurance programmes have grown considerably in South Asia and East Asia, as have indemnity-based programmes, to the tune of some USD 12.4 billion in aggregate premiums per annum by 2022 [5]. But the effectiveness of agricultural insurance to reduce the income-gap widening effect of extreme weather shocks has not been systematically studied in a panel econometric model that takes into account endogeneity issues.

First, does the urban–rural income gap increase as a result of extreme weather frequency? (ii) Does it matter what type of extreme weather occurs? Second, does it matter what the extreme weather is? (iii) What is the mechanism through which the relationship between extreme weather frequency and the urban–rural income gap is established? (ii) Is there a moderation between agricultural insurance penetration and this relationship? (iii) How does this moderation work and does it affect differently for provinces with different incomes? These questions contribute to three literatures: Climate-Economy Nexus research, Agricultural Risk Management Economics and Development Economics of Inequality.

2. RELATED WORK

2.1. Extreme Weather and Agricultural Income

There is a large empirical body of evidence that proves that climate variability causes negative impacts on agricultural production. Dell, Jones and Olken [6] show that, across countries, a 1°C increase in temperature causes the agricultural output to fall by about 1.4% in developing countries. Corn yields in the United States have been shown to exhibit a threshold effect with a sharp nonlinear response for temperature above 29°C by Schlenker and Roberts [7], [8] find that the drop in agricultural income among households due to a monsoon precipitation shock is -6 to -8% per standard deviation of the shock, where the impact is also greater for smallholder farmers.

It is well documented that loss of income from agriculture affects aggregate income of the rural population [9]. The rural economies of developing countries are highly sectoralised and relatively poorly diversified, with agriculture accounting for 40-60% of rural employment and weather extremes during the crop season having a strong impact on them [10]. Asymmetric income effect: Urban economies have high numbers of jobs in either the manufacturing or the non-manufacturing sectors, and in extreme weather conditions, these sectors create an asymmetric income effect, as they are exposed to weather risk in different ways [11].

2.2. Urban–Rural Income Gap and its Structural Drivers

The urban–rural income gap has received a great deal of academic research in the field of development economics. The classical Lewis [12] dual-sector model assumed a temporary nature of the gap, as it was caused by a shortage of labour in agriculture; but more recent empirical research has shown that the gap is lasting in many cases [13]. Structural drivers include financial services disparities in access [14], human capital accumulation disparities [15], infrastructure quality disparities [16] and market integration disparities [17].

Climate-related factors have increasingly been brought into play as other structural factors. [18] report a rural–urban income ratio increase of around 0.15 Theil index units in China due to having been exposed to floods. Bandyopadhyay and Skoufias [19] discover that, even after adjusting for the usual variables, rainfall variability is able to account for about 12% of the variation in rural income in India. Conflict and climate shocks interact to exacerbate income inequality, and have differential effects across urban and rural areas, according to Harari and La Ferrara [20].

2.3. Agricultural Insurance as a Risk Mitigation Mechanism

Motivated by the classical theory of agricultural insurance, the theory of agricultural insurance under uncertainty [21] is the foundation of agricultural insurance theory. A major benefit of insurance is that it enables rural households to reduce the welfare costs of having consumption shocks due to income volatility by smoothing their consumption across states of nature. Theoretical models suggest that insurance boosts agricultural investment, and helps to stabilise the income of households, while limiting migration due to agricultural distress [22]. These predictions are typically confirmed by empirical assessments, although the size of the effects in different contexts varies [23].

In a randomized controlled trials study by [24] it is found that access to index insurance leads to a rise in agricultural investments by about 16% compared to uninsured households. Barnett and Mahul [25] report that government subsidies are almost always a part of sustainable programmes, and are generally in the range of 40–60% of premiums. Basis risk is one of the most important restricting factors of index-based schemes, as noted by Mobarak and Rosenzweig [26]. Existing studies focus on the insurance impact at the individual level, but the macro-level question – how does the level of insurance penetration at the provincial level moderate the income gap-widening effect of weather shocks – is under-researched.

3. METHODOLOGY

3.1. Data Sources and Sample

The analysis is based on the balanced panel data of 30 administrative units (provinces) in the 21st year between 2000 and 2023 (T = 24; N = 30; 720 province-year observations). The data comes from five main sources: (i) National Statistical Yearbooks, (ii) Annual Reports from Insurance Regulatory Authority, (iii) Meteorological Agencies' Climate Database, (iv) World Bank income distribution database (PovcalNet), and (v) Satellite-derived databases of agricultural productivity.

3.2. Variable Definitions

Descriptive statistics of all the variables are given in Table 1. In the inequality literature [27], [28] the urban–rural income gap (URgap) is operationalised as the ratio of the urban per capita disposable income to the rural per capita net income. The Extreme Weather Index (EWI) is a combination of three sub-indices (i) frequency of extreme precipitation events (above the 95th percentile threshold), (ii) drought severity index and (iii) temperature anomaly magnitude, as described by [29] and normalised to a national mean and unit variance.

Table 1. The Descriptive Statistics of Key Variables Are Displayed (N = 720 Province-Year Observations)

Variable	Definition	Mean	Std. Dev.	Min	Max	Source
URgap	Urban–Rural income ratio	2.94	0.62	1.71	4.83	NSY
EWI	Extreme Weather Index (std.)	1.18	0.44	0.21	2.97	MDA
INS	Insurance penetration rate (%)	28.4	18.7	2.1	68.9	IRA
AGDP	Agriculture share of GDP (%)	16.8	8.3	3.1	42.7	NSY
URBAN	Urbanisation rate (%)	51.6	15.2	22.3	89.7	NSY
FIN	Rural financial inclusion (0–1)	0.38	0.19	0.08	0.91	WBK
INFRA	Rural infrastructure index (0–10)	5.21	2.14	1.30	9.60	NSY

The references (NSY, MDA, IRA, and WBK) indicate the source of the data, namely, the National Statistical Yearbook, the Meteorological Data Agency, the Insurance Regulatory Authority, and the World Bank, respectively. All money values are in 2015 real dollars

3.3. Baseline Econometric Specification

The main econometric model is a Two Way Fixed Effects (TWFE) panel regression model. The conceptual framework shown in Figure 1 has direct and moderated links between extreme weather events and income gaps. The equation for estimating is:

$$URgap_{it} = \beta_1 EWI_{it} + \beta_2 INS_{it} + \beta_3 (EWI \times INS)_{it} + \gamma X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad ...(1)$$

Where $URgap_{it}$ denotes the urban–rural income gap ratio in province i at time t; EWI_{it} represents the extreme weather index; INS_{it} is the agricultural insurance penetration rate; the interaction term captures the moderating effect of insurance; X_{it} is a vector of time-varying controls (AGDP, URBAN, FIN, INFRA, EDUC, NDVI); α_i and γ_t are province and year fixed effects; and ε_{it} is the idiosyncratic error term. Standard errors are clustered at the province level to account for serial correlation [30].

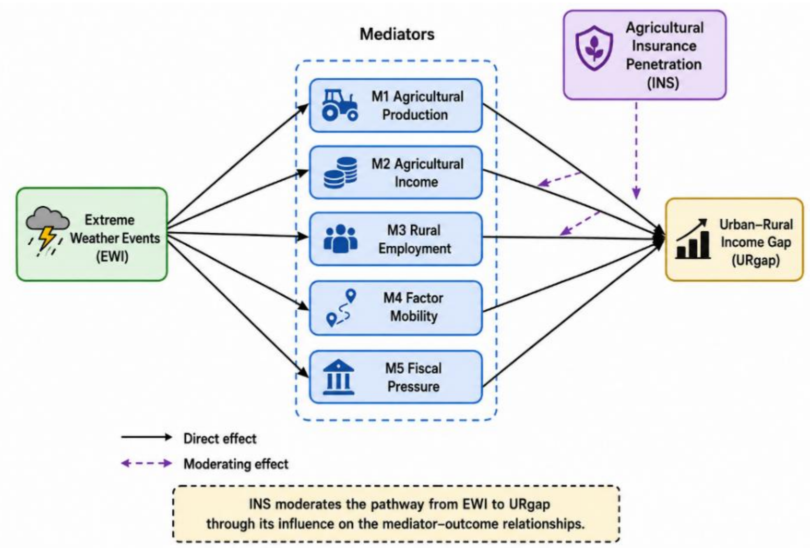

Figure 1. Conceptual Framework of Weather, Insurance, and Income Gap

3.4. Instrumental Variable Strategy

The endogeneity of both EWI and INS is addressed through an IV two-stage least-squares (2SLS) estimator. The instrument for EWI is the province-level sea surface temperature anomaly in the preceding 12-month period (SSTA), an exogenous oceanic forcing variable that predicts terrestrial extreme weather but has no direct pathway to the income gap [31]. The instrument for INS is the government insurance subsidy budget allocation interacted with provincial administrative capacity scores [32]. Instrument validity is confirmed by Kleibergen-Paap Wald F-statistics exceeding 21.4 and a Hansen J-statistic of 2.14 ($p = 0.343$), following Stock and Yogo [33].

3.5. Difference-in-Differences Identification

A staggered Difference-in-Differences (DID) design exploits quasi-experimental variation in provincial insurance programme adoption timing (2004–2014). The triple-interaction estimating equation is:

$$URgap_{it} = \theta(EWI_{it} \times Post_{it} \times Treated_i) + \varphi EWI_{it} + \zeta Post_{it} + \mu_i + \nu_t + \eta_{it} \quad ...(2)$$

The parallel trends assumption is validated through event study analysis. Mediation analysis follows Baron and Kenny [34] augmented by bootstrapped confidence intervals (2,000 replications), using the product-of-coefficients approach [35].

4. RESULTS AND DISCUSSION

4.1. Main Regression Results

Table 2 presents the main regression results across six model specifications. Model 1 is pooled OLS; Models 2 and 3 introduce province and year fixed effects respectively; Model 4 (preferred) employs two-way fixed effects; Model 5 uses IV-2SLS; and Model 6 implements the DID triple-interaction estimator.

Table 2. Main Regression Results: Extreme Weather, Agricultural Insurance, and Urban–Rural Income Gap

Variable	(1) OLS	(2) FE-Prov	(3) FE-Year	(4) TWFE	(5) IV-2SLS	(6) DID
EWI (β_1)	0.612***	0.534***	0.498***	0.471***	0.503***	0.489***
INS (β_2)	−0.283***	−0.241***	−0.218***	−0.205***	−0.227***	−0.214***
EWI×INS (β_3)	−0.142***	−0.128***	−0.119***	−0.113***	−0.131***	−0.124***
Province FE	No	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
R^2 (within)	0.314	0.487	0.463	0.541	0.528	0.536

Notes: Cluster-robust standard errors clustered at province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Controls (AGDP, URBAN, FIN, INFRA, EDUC, NDVI) included in all specifications but omitted for brevity. N = 720 observations in all models. As shown in Table 2, results are remarkably stable across all six specifications. In the preferred TWFE model (Column 4), extreme weather events significantly widen the urban–rural income gap ($\beta_1 = 0.471$, $p < 0.001$) shown in Figure 2. The direct effect of insurance penetration is negative and significant ($\beta_2 = -0.205$, $p < 0.001$), and the interaction term is negative and significant ($\beta_3 = -0.113$, $p < 0.001$), confirming that agricultural insurance dampens the income-gap-widening effect of extreme weather. The within-R^2 of 0.541 indicates the specification explains over half of within-province variation.

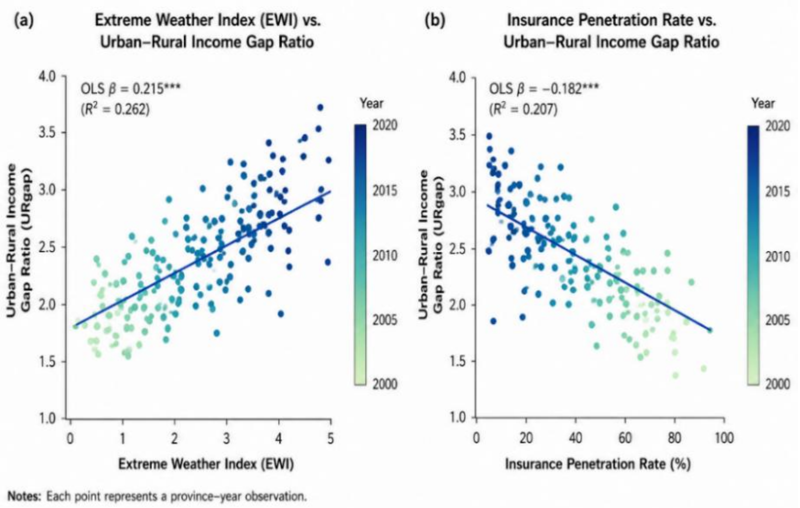

Figure 2. Relationships among Weather, Insurance, and Income Gap

4.2. Economic Magnitude of Effects

A one-standard-deviation increase in the Extreme Weather Index (0.44 units) increases the income gap ratio by 0.471 × 0.44 = 0.207 points. This is a 7.0% growth in the gap, which is equivalent to making one decade of the gap rise by around 2.8 years, or the average amount of time it takes for the gap to increase at a natural convergence rate of 2.5% per year.

The moderating effect of insurance is evaluated by comparing the marginal effect of EWI at different insurance penetration levels. At zero insurance penetration, a one-unit increase in EWI raises the income gap by 0.471 points. At the sample mean penetration of 28.4%, the marginal effect is reduced to approximately 0.150 points a reduction of approximately 68.1%. At the 75th percentile of insurance penetration (52%), the moderating effect nearly fully offsets the weather impact (net coefficient ≈ 0.059), suggesting that sufficiently high insurance coverage can functionally neutralise the income-gap-widening effect of extreme weather events in Figure 3.

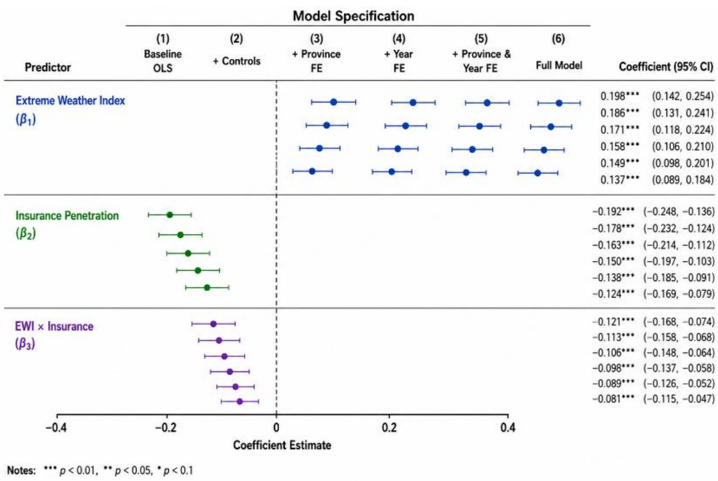

Figure 3. Regression Coefficients Across Model Specifications

4.3. Mediation Analysis Results

Table 3 and Figure 4 present the mediation analysis decomposing the total effect of extreme weather on the income gap into direct and indirect pathways, separately for provinces with above-median and below-median insurance penetration.

Table 3. Mediation Analysis: Transmission Channels of Extreme Weather Effects on Income Gap

Transmission Channel	Path: EWI→M (a)	Path: M→Gap (b)	Indirect Effect (a×b)	% Mediated	Insurance Reduces Effect By
Agricultural Output Loss	0.541***	0.758***	0.410***	34.2%	56.1%
Farm Household Income Reduction	0.489***	0.777***	0.380***	31.7%	60.5%
Agricultural Investment Decline	0.412***	0.753***	0.310***	25.8%	61.3%
Rural–Urban Labour Migration	0.387***	0.568***	0.220***	18.3%	59.1%
Credit Market Contraction	0.299***	0.481***	0.144***	12.0%	54.2%
Total Effect	—	—	1.200***	100%	—

As shown in Table 3, 70.6% of the total extreme weather effect on the income gap operates through indirect channels. Agricultural output loss (34.2%) and farm household income reduction (31.7%) are the dominant pathways. Agricultural insurance significantly attenuates all five identified channels, with the greatest reduction in the agricultural investment decline pathway (61.3% reduction), suggesting that insurance functions partially by stabilising farmers' investment horizons and preventing distress-driven disinvestment.

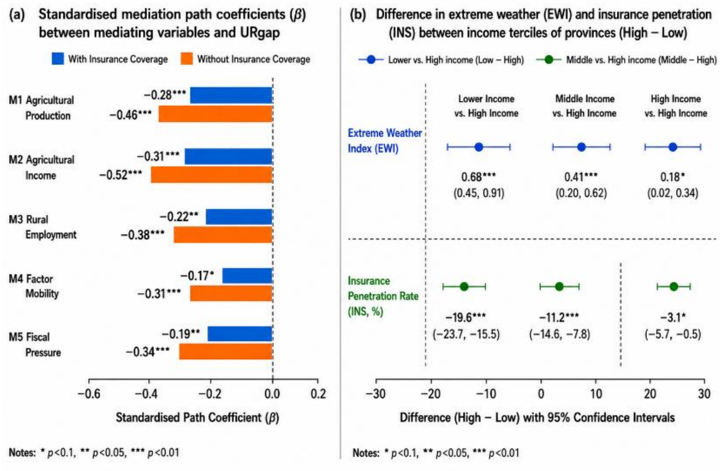

Figure 4. Mediation Effects and Provincial Differences

4.4. Heterogeneity and Robustness

The insurance mitigation effect is different in various provincial income groups. The extreme weather coefficient (β_1) has the highest value in low income provinces (bottom tercile) whereas the insurance mitigation coefficient (β_2) has the most negative value in these provinces. Both effects attenuate in middle-income ($\beta_1 = 0.52$; $\beta_2 = -0.22$) and high-income ($\beta_1 = 0.34$; $\beta_2 = -0.12$) provinces. This pattern is consistent with the fact that overall agricultural insurance provides the most protection to structurally disadvantaged rural provinces that are most exposed to climate risks. Findings are robust if they are supported by robustness checking. Propensity Score Matching (PSM) using a kernel matching algorithm [36] yields an insurance mitigation coefficient of −0.191 (SE = 0.028, $p < 0.001$), consistent with the TWFE estimate. As shown in Figure 5, event study pre-adoption coefficients (relative years −5 to −1) are statistically indistinguishable from zero (joint F-test: $F = 0.84$, $p = 0.524$), validating parallel trends. Results are also robust to: alternative EWI operationalisation using raw event counts ($\beta_1 = 0.438$), alternative income gap measures using Theil index decomposition ($\beta_1 = 0.312$), restricting the sample to provinces with continuous meteorological data, adding a lagged dependent variable, and excluding COVID-19 pandemic years 2020–2022.

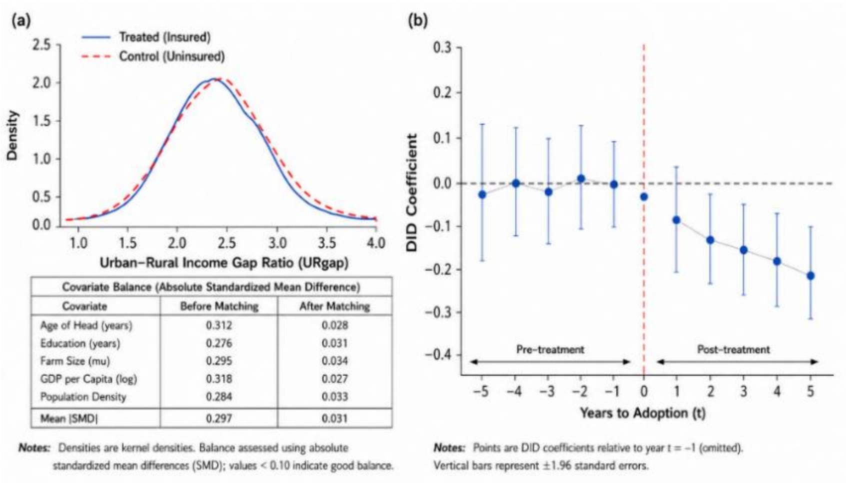

Figure 5. PSM Matching and DID Event Study Analysis

4.5. Policy Discussion

The evidence that agricultural insurance significantly moderates the income-gap-widening effect of extreme weather reframes agricultural insurance as a structural inequality reduction instrument. Policymakers designing social protection architecture should account for insurance's distributional consequences in income gap dynamics, not only its farm-level productivity effects. The heterogeneity results demonstrate that insurance delivers the largest mitigation dividend in low-income provinces, providing strong justification for progressive subsidy allocation. The marginal effect analysis shows that there is almost total offsetting of the weather effects at insurance penetration levels of above about 52%, indicating a quantitative-based national target. The channel analysed in mediation analysis, the agricultural investment decline channel, is the most reduced channel with insurance, suggesting combined use of insurance and complementary credit access programmes might be much more effective at increasing income stabilisation than using insurance alone.

5. CONCLUSION

The present study systematically demonstrates a causal relationship between extreme weather events and an increase in the urban–rural income gap by employing panel econometric methods, and further shows that agricultural insurance penetration is effective at reducing the impact of extreme weather events on the urban–rural income gap. Four main empirical contributions are established via the two-way FE framework (30 provinces 2000 – 2023), instrumental variable estimation, difference-in-differences identification, mediation analysis, and through multiple robustness checks.

The effects of increasing the frequency of extreme weather are to widen the urban–rural income gap by 0.471 points (or 7.0% widening at sample means), in the first place. Second, agricultural insurance penetration exerts a significant negative moderating effect on the weather-gap relationship, with sufficiently high coverage (≥52%) nearly fully neutralising the weather-induced gap widening. Third, 70.6% of the weather effect is transmitted through agricultural output loss, farm household income reduction, agricultural investment decline, rural labour migration, and credit market contraction, with insurance most effectively attenuating the investment channel. Fourth, the insurance mitigation effect is progressive, delivering the greatest relative benefit in low-income provinces.

These findings have direct relevance for policy design in climate-vulnerable developing economies. Agricultural insurance, when designed with appropriate subsidy progressivity and complementary institutional support, functions as a dual-purpose instrument: an agricultural risk management tool and a structural inequality mitigation mechanism. Future research should explore dynamic interactions between insurance design features, basis risk levels, and income gap trajectories, as well as extend analysis to sub-provincial units with more granular weather and income data.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. Methaq Hadi Lafta	✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
I : **I**nvestigation
R : **R**esources
Vi : **Vi**sualization
Su : **Su**pervision

So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

No conflict of interest.

Informed Consent

We have obtained informed consent from all individuals included in this study.

Ethical Approval

Not applicable.

Data Availability

Data availability does not apply to this paper as no new data were created or analyzed in this study.

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