

Spatially Heterogeneous Climate Shocks and Regional Economic Vulnerability: A Spatial Panel Econometric Analysis of El Niño Impact Across Indonesian Provinces

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Abstract

This study examines whether El Niño climate shocks generate spatially heterogeneous economic impacts across provinces in Indonesia. The analysis employs a spatial panel econometric framework that leverages the geographically polarized structure of El Niño impacts in Indonesia, characterized by extreme drought in the southern and western provinces and flood anomalies in the eastern archipelago. The dataset covers 38 provinces over the period 2000 to 2025, using a Spatial Durbin Model (SDM) estimated via Maximum Likelihood. The study decomposes the total effect of El Niño intensity, measured by the average Oceanic Niño Index (ONI) from April to October, into direct effects and indirect effects in the form of spatial spillovers on provincial real GDP per capita growth, poverty rates, and the share of agricultural value added. The estimation results indicate that a one unit increase in ONI reduces real GDP per capita growth by 0.84 percentage points in directly affected provinces, while spatial spillover effects add a further loss of 0.38 percentage points in neighboring provinces. These effects weaken significantly in provinces with stronger irrigation infrastructure and higher levels of economic diversification. The findings suggest that climate risks in an archipelagic country operate through spatially interconnected channels and are systematically overlooked by uniform national policies. The results provide empirical evidence to inform region based disaster preparedness allocation and interprovincial climate resilience coordination in Indonesia.

Keywords: El Niño Southern Oscillation; spatial panel data; Spatial Durbin Model; regional economic vulnerability; climate shocks

JEL Classification: C33; Q54; R11; R58

Introduction

Does El Niño generate economically distinct impacts across the regions that constitute a large archipelagic country? Globally, climate anomalies rooted in the El Niño Southern Oscillation (ENSO) are known to reshape agricultural output, commodity prices, and national growth trajectories in tropical countries. However, the existing empirical literature generally treats these impacts as spatially uniform by aggregating economic responses at the national level, thereby obscuring the geographic heterogeneity that lies at the core of climate risk in archipelagic economies. Indonesia exemplifies this challenge acutely. The country stretches more than 5,000 kilometers across two oceans, the Pacific Ocean and the Indian Ocean. During El Niño episodes, its physical consequences are sharply divided, as southwestern provinces face extreme drought and forest fires, while northeastern islands experience anomalous rainfall and flash floods in what the climate literature describes as a paradox of simultaneous extremes (Floridi et al., 2025).

This study addresses this gap by examining the spatially heterogeneous economic impacts of El Niño across 38 Indonesian provinces over the period 2000 to 2025. It exploits the sharp polarization in climate exposure to identify both local effects and cross provincial spillover effects. The analysis is guided by three main questions. First, does El Niño intensity generate statistically distinct effects on provincial GDP growth, poverty rates, and agricultural productivity that vary systematically across climate zones? Second, are there significant spatial spillover effects such that the economic vulnerability of a province is influenced by El Niño exposure in neighboring provinces? Third, which provincial structural characteristics significantly moderate the magnitude of climate induced vulnerability, such as irrigation infrastructure coverage, economic diversification, and agricultural dependence?

The study employs a Spatial Durbin Model (SDM) estimated using Maximum Likelihood Estimation (MLE). The spatial weighting matrix is constructed based on queen contiguity and interprovincial economic trade linkages. This framework allows the decomposition of the total effect of El Niño, proxied by the average ONI from April to October, into direct effects on a province's own outcomes and indirect spillover effects transmitted through neighboring provinces. The choice of the SDM over conventional panel models is motivated by diagnostic evidence of significant spatial autocorrelation in provincial GDP residuals, confirmed by annual Moran's I statistics over the period 2000 to 2025.

El Niño intensity data are obtained from the NOAA Climate Prediction Center. Provincial GDP and poverty data are sourced from Statistics Indonesia (BPS). The spatial weighting matrix is constructed using provincial administrative shapefiles and interregional trade flow tables published by BPS. The April to October aggregation window follows established practice in the Indonesia climate economics literature (Apriyana et al., 2019; Malau et al., 2021), as this period captures the peak of drying and flooding anomalies associated with El Niño across the archipelago.

Cross sectional SDM estimates for the period 2000 to 2025 show that El Niño consistently reduces real GDP per capita growth in southern and western Indonesian provinces. The largest effects, exceeding 1.3 percentage points per unit increase in ONI, are concentrated in major rice producing zones in Java and Nusa Tenggara. Direct effect estimates further reveal that the magnitude of economic losses declines significantly in provinces with stronger irrigation infrastructure and lower agricultural dependence. In addition, indirect spillover effects transmitted through interprovincial trade and labor mobility account for a substantial share of total losses in neighboring provinces. These findings have direct implications for the design of intergovernmental emergency response coordination.

This study makes three main contributions. First, it provides new subnational evidence on the spatially differentiated economic consequences of El Niño in a large developing country, extending country level findings from Callahan and Mankin (2023) and Smith (2017) to the provincial scale. Second, it is the first to apply the Spatial Durbin Model in the context of ENSO induced vulnerability across Indonesian provinces, directly addressing the spatial heterogeneity gap identified by Floridi et al. (2025). Third, by constructing a dual spatial weighting matrix that integrates geographic contiguity with economic distance, the study produces estimates that are robust to alternative assumptions about how spatial interactions operate in an archipelagic setting.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides background on El Niño dynamics and their regional differentiation across the Indonesian archipelago. Section 4 outlines the empirical specification. Section 5 describes the data. Section 6 presents the results. Section 7 concludes.

Literature Review

This study contributes to three strands of literature: the macroeconomic and regional economic impacts of El Niño, the application of spatial econometric methods to climate shocks, and the structural determinants of economic vulnerability to climate variability in developing countries. A growing body of research has established that El Niño reduces economic growth, particularly in tropical developing economies. Callahan and Mankin show that El Niño events exert persistent downward pressure on GDP, linking global income losses of 4.1 trillion US dollars to the 1982 to 1983 episode and 5.7 trillion US dollars to the 1997 to 1998 episode. Liu et al. extend these findings using nonlinear climate economy models and project that increased ENSO variability under climate change will generate additional median losses of 33 trillion US dollars over the remainder of the twenty first century. Smith and Ubilava provide the most directly comparable benchmark by examining ENSO effects on growth across 69 developing countries and find that a one degree increase in Niño3.4 sea surface temperature reduces annual growth by one to two percentage points in tropical regions, with particularly pronounced effects in the Asia Pacific. Dufrénot et al. extend this analysis within a global augmented vector autoregression framework and confirm that El Niño stimulates output with minimal inflationary pressure, whereas La Niña amplifies food price inflation.

Despite substantial evidence at the national level, subnational analyses of the economic geography of El Niño remain limited. Malau et al. examine the impact of ENSO on food crop prices across 23 Indonesian provinces using static panel data and find that El Niño raises the prices of rice, sweet potatoes, and mung beans more strongly than La Niña. However, their analysis treats provinces as independent units and does not account for spatial interactions. Apriyana et al. document that ENSO and Indian Ocean Dipole events delay rice planting calendars differently in West Sumatra compared to West Java, implying regionally differentiated economic consequences that cannot be captured by standard panel models (Floridi et al., 2025). Floridi et al. provide the most comprehensive review to date of El Niño and positive Indian Ocean Dipole effects across the Indo Pacific, explicitly concluding that the absence of evidence on spatially differentiated subnational impacts represents the most pressing gap in the literature.

The application of spatial econometric methods to climate economy relationships has expanded rapidly in recent years. Acacha-Acakpo et al. (2024) apply a dynamic Spatial Durbin Model to examine how temperature and precipitation influence regional economic disparities across provinces in Benin and find significant positive spatial externalities in both the short and long run. Chen estimate a Spatial Durbin Model using provincial data from China and find that climate change generates positive spillovers at

the national level but produces asymmetric indirect losses in less developed regions. Fan and Ma use spatial error and Spatial Durbin models to estimate weather effects on milk production at the US state level and show that spatial panel specifications outperform conventional models in prediction. Andriyana et al. (2024). and Falah et al. (2024) apply extended Spatial Durbin frameworks to predict rainfall patterns in Java and confirm that spatial dependence is pervasive in Indonesian climate data, and that ignoring it leads to biased coefficient estimates. However, none of these studies focus on the economic consequences of El Niño through a spatial econometric lens in a multi provincial archipelagic context.

A third relevant strand of literature examines the structural determinants of climate vulnerability. Ubilava demonstrate that ENSO shocks have amplified and persistent effects on commodity prices produced in tropical regions, consistent with storage based economic mechanisms. Brunner shows that a one standard deviation ENSO shock increases real commodity price inflation by 3.5 to 4 percentage points and accounts for approximately 20 percent of commodity price movements. Gurazada et al. (2024) find that concurrent El Niño and positive Indian Ocean Dipole conditions reduce the production of multiple cereal crops in India, with impacts that vary substantially by crop type and district level geography. These findings suggest that the structural composition of provincial economies, particularly the share of rainfed agriculture and irrigation capacity, should moderate provincial economic vulnerability to El Niño shocks. This hypothesis is tested directly in the empirical analysis of this study.

Overall, the existing literature identifies three gaps that this study addresses. First, no study has applied spatial panel econometric models to the subnational economic impacts of El Niño in Indonesia. Second, the spatial spillover dimension of ENSO induced vulnerability, namely the extent to which exposure in one province propagates to neighboring provinces through trade, labor mobility, and fiscal linkages, has not been examined. Third, the moderating roles of irrigation infrastructure and economic diversification in shaping climate vulnerability at the provincial level have not been empirically identified within a spatial framework. This study addresses all three gaps using 25 years of provincial panel data and a Spatial Durbin Model.

2.1. El Niño Dynamics and the Indonesian Archipelago

The El Niño Southern Oscillation (ENSO) is driven by anomalous warming of sea surface temperatures in the equatorial Pacific Ocean. During El Niño episodes, oceanic heat anomalies act as a large scale atmospheric pump that draws moisture away from the western Pacific and weakens the convective activity that normally drives precipitation over Indonesia. The resulting physical consequence is a sharp decline in rainfall across most of the archipelago, with effects typically peaking between April and October. This period defines the Indonesian dry season and serves as the primary analytical window for this study.

The Oceanic Niño Index (ONI), published monthly by the NOAA Climate Prediction Center, measures the three month running mean of sea surface temperature anomalies in the Niño3.4 region relative to a 30 year climatological baseline. An El Niño event is conventionally defined as five consecutive overlapping three month periods with ONI values exceeding +0.5 degrees Celsius. Over the sample period from 2000 to 2025, significant El Niño events occurred in 2002 to 2003, 2004 to 2005, 2006 to 2007, 2009 to 2010, 2014 to 2015, 2015 to 2016, 2018 to 2019, and 2023 to 2024. The 2015 to 2016 episode was the strongest in the modern observational record, with a peak ONI of +2.6 degrees Celsius. The projected 2025 to 2026 episode has already exhibited ONI values above +2.3 degrees Celsius and has been classified by Badan Riset dan Inovasi Nasional as potentially rivaling the 2015 to 2016 super El Niño.

Beyond ENSO, a secondary climate driver known as the Indian Ocean Dipole (IOD) also modulates Indonesia's rainfall patterns. The IOD measures the difference in sea surface temperatures between the western and eastern Indian Ocean. During positive IOD events, defined by a Dipole Mode Index (DMI) exceeding +0.4 degrees Celsius, cooling of sea surface temperatures west of Sumatra reduces local evaporation and disrupts a critical moisture source for western Indonesia. Importantly, positive IOD events tend to coincide with El Niño, creating a dual suppression of moisture availability that amplifies drought severity beyond what either phenomenon would produce independently. The years 2015 and 2019 stand out as the most severe compound anomaly years in the sample, as concurrent El Niño and strong positive IOD conditions produced some of the most extreme fire and drought events in Indonesia's recorded history.

2.2. Geographic Polarization of El Niño Impacts in Indonesia

A defining feature of El Niño's spatial impact in Indonesia is its internally polarized character. The standard assumption that drought conditions affect the entire archipelago uniformly does not hold at the subnational level. The underlying physical dynamics differ markedly between the western and eastern regions, producing what Floridi et al. (2025) describe as heterogeneous intra national patterns. This structure is systematically obscured in national level analyses that rely on aggregated data.

Three geographically distinct crisis zones characterize Indonesia's El Niño landscape. The southern zone, encompassing Java, Bali, and Nusa Tenggara, experiences extreme drought and groundwater depletion that directly threaten national rice supply, as this region accounts for approximately 60 percent of Indonesia's rice production. The western zone, including Sumatra and Kalimantan, faces widespread forest and land fires known as Karhutla. Persistently dry conditions across peat dominated landscapes create ideal conditions for biomass ignition in this zone. The eastern zone, covering Sulawesi, Maluku, and Papua, paradoxically experiences concentrated anomalous rainfall during El Niño years, as displaced moisture convergence zones generate localized flooding and landslide risks during a period otherwise classified as the dry season for the rest of the archipelago.

This three zone spatial polarization creates a unique identification environment. Within a single El Niño year, Indonesia simultaneously exhibits agricultural losses from drought, environmental and health costs from fires, and infrastructure damage from flooding, all of which can be traced to the same climatic forcing. It is precisely this spatial variation in exposure that the Spatial Durbin Model is designed to exploit, as it enables identification of locally differentiated economic responses while also capturing how shocks in one zone propagate to economically connected neighboring provinces.

Research Methods

3. Empirical Specification

The empirical strategy of this study exploits both temporal and spatial variation in El Niño intensity across 38 Indonesian provinces. It begins with a baseline panel regression and progressively introduces spatial structure, first through a Spatial Lag Model and subsequently through a Spatial Durbin Model, to capture both direct and indirect effects of El Niño shocks on provincial economic outcomes.

3.1. Baseline Specification

The initial estimation employs a non spatial fixed effects panel model to establish baseline estimates of the direct impact of El Niño on provincial economic outcomes. The estimating equation is as follows:

$$y_{it} = \alpha_i + \gamma_t + \beta \cdot ONI_t + X_{it}'\delta + \varepsilon_{it} \dots \dots \dots (1)$$

In this equation, y_{it} represents the outcome variable for province i in year t , specifically real GDP per capita growth, poverty rate, or the share of agricultural value added. The term α_i denotes province fixed effects that capture time invariant geographic and structural characteristics, while γ_t represents year fixed effects that absorb common macroeconomic shocks. The variable ONI_t is the average ONI over the April to October period, serving as a measure of El Niño intensity in year t . The vector X_{it} includes time varying provincial controls, such as the agricultural dependence index, irrigation infrastructure index, economic diversification index (HHI), population density, provincial government expenditure, as well as national level controls including oil prices, the IDR to USD exchange rate, and the agricultural production index.

The primary identification challenge in Equation (1) is the presence of spatial autocorrelation. If El Niño shocks generate residuals that are correlated across neighboring provinces, the baseline estimates become inefficient and statistical inference is invalid. This pattern is confirmed through Moran's I tests. In addition, the baseline model cannot distinguish between the direct economic effects of El Niño on a given province and indirect effects operating through its economic linkages with affected neighbors.

3.2. Spatial Durbin Model

To address spatial dependence and disentangle direct from indirect effects, the study specifies a Spatial Durbin Model as follows:

$$y_{it} = \rho W y_{it} + \alpha_i + \gamma_t + \beta ONI_t + \theta W ONI_t + X_{it}' \delta + W X_{it}' \phi + u_{it} \dots \dots \dots (2)$$

In this specification, W is an $N \times N$ row normalized spatial weighting matrix. The parameter ρ is the spatial autoregressive coefficient capturing dependence of a province's outcome on the outcomes of its spatially weighted neighbors. The parameter θ represents the coefficient on the spatially lagged El Niño index. The Spatial Durbin Model nests the Spatial Lag Model when θ and ϕ are equal to zero and reduces to a Spatial Error Model under specific parameter restrictions. Model selection among these alternatives is based on Robust Lagrange Multiplier tests applied to the residuals of Equation (1).

Equation (2) is estimated using Maximum Likelihood Estimation for spatial panel data with province and year fixed effects. From the SDM estimates, the study computes the full matrix of partial derivatives to decompose the total effect of El Niño into three components. The first component is the average direct effect, capturing the impact of ONI on a province's own economic outcome, averaged across all provinces. The second component is the average indirect effect, measuring spatial spillovers arising from El Niño exposure in neighboring provinces. The third component is the average total effect, defined as the sum of direct and indirect effects. Standard errors for these decomposed effects are obtained through Monte Carlo simulation with 1,000 draws from the asymptotic distribution of the estimated coefficient vector.

3.3. Spatial Weighting Matrices

The study constructs two alternative spatial weighting matrices to assess the robustness of results under different assumptions about spatial interaction. The first is a queen contiguity matrix, denoted W_{queen} , which assigns a weight of one to province pairs that share either a common border or vertex and zero otherwise, and is then row normalized so that each row sums to one. This matrix captures geographic proximity as the primary channel of spatial interaction, consistent with climate spillover mechanisms whereby drought or fires in one province directly affect labor markets and agricultural inputs in adjacent provinces.

The second is an economic distance matrix, denoted W_{econ} , constructed from interregional trade flow data in regional input output tables published by Badan Pusat

Statistik. Following the economic geography literature, bilateral trade flows are normalized by total provincial trade to obtain a symmetric measure of economic connectivity between province pairs. This matrix captures the channel through which demand contractions in El Niño affected provinces propagate to their trading partners, regardless of physical adjacency. Baseline estimates use W_{queen} , while W_{econ} is employed for robustness checks.

The study also estimates the Spatial Durbin Model separately for two ENSO regime subsamples. The first subsample corresponds to the El Niño regime, defined as years with April to October ONI above +0.5 degrees Celsius. The second subsample corresponds to neutral or La Niña conditions, including all remaining years. This split tests whether the spatial structure of climate economic interdependence differs systematically between active El Niño periods and baseline conditions, thereby addressing potential nonlinearities in the ENSO economy relationship documented by Ubilava (2018).

3.4. El Niño Intensity and Climate Variables

The primary climate variable is the Oceanic Niño Index (ONI), obtained from the NOAA Climate Prediction Center. ONI measures the three month moving average of sea surface temperature anomalies in the Niño3.4 region relative to a 30 year climatological baseline. Monthly ONI values are aggregated to an annual frequency by averaging over the April to October window, which coincides with the Indonesian dry season and captures the peak atmospheric teleconnection between Pacific sea surface temperature anomalies and precipitation deficits in Indonesia.

The Dipole Mode Index (DMI), sourced from Japan Agency for Marine-Earth Science and Technology, is used as an additional climate variable and to construct a compound anomaly dummy. The compound anomaly dummy is defined as years in which ONI exceeds +0.5 degrees Celsius and DMI exceeds +0.4 degrees Celsius simultaneously. Over the 26 year sample, nine years satisfy this joint condition, including the particularly severe episodes of 2015 and 2019.

3.5. Provincial Economic Variables

Provincial Gross Regional Domestic Product (GRDP) at constant 2010 prices is obtained from Badan Pusat Statistik and covers 38 provinces from 2000 to 2025. GRDP per capita is calculated by dividing constant price GRDP by provincial population, based on population projection series from BPS derived from the 2020 Census.

The poverty rate, defined as the percentage of the population below the provincial poverty line, is obtained from the March rounds of the National Socioeconomic Survey (Susenas) conducted by BPS to ensure temporal consistency across years. The share of agricultural value added is computed as the ratio of the contribution of agriculture, forestry, and fisheries to total provincial GRDP, based on sectoral GRDP accounts from BPS. This variable serves both as a dependent variable capturing the direct impact of El Niño on the agricultural sector and as a moderating variable representing an index of agricultural dependence in the structural heterogeneity analysis.

3.6. Structural Moderating Variables

Three provincial structural characteristics function as moderators of El Niño vulnerability.

First, the irrigation infrastructure index is calculated as the area of technical irrigation in hectares per 1,000 hectares of agricultural land, based on annual data from the Ministry of Agriculture and the Ministry of Public Works and Housing. Provinces with higher irrigation coverage are expected to sustain agricultural output during drought years, as irrigated fields can rely on stored water rather than rainfall alone.

Second, the economic diversification index is measured using the Herfindahl Hirschman Index (HHI), calculated from sectoral GRDP across 17 industries. Lower HHI values indicate greater economic diversification and lower sensitivity to agricultural shocks.

Third, population density, measured in persons per square kilometer, proxies for a province's capacity for emergency response, redistribution, and rapid economic recovery following climate shocks.

3.7. Macroeconomic Controls

Three national level controls are included to absorb general macroeconomic fluctuations correlated with El Niño cycles and economic growth. The annual average Brent crude oil price in US dollars per barrel is obtained from the World Bank Commodity Price database, also known as the Pink Sheet. The IDR to USD exchange rate is measured as the annual average midpoint exchange rate from Bank Indonesia's Statistics on Economic and Financial Data. The national agricultural production index, with base period 2014 to 2016 equal to 100, is sourced from FAOSTAT and serves as a proxy for aggregate domestic supply conditions. Provincial government expenditure, measured as realized total regional budget spending, is obtained from the Directorate General of Fiscal Balance at the Ministry of Finance.

Table 1.
Descriptive Statistics by Year and Climate Zone

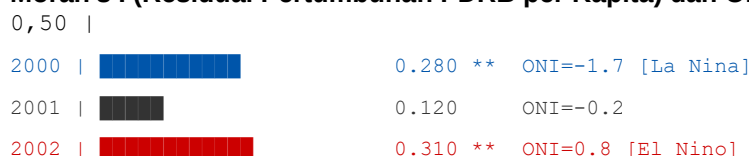
Variable	Full Sample Mean (SD)	Southern Zone Mean (SD)	Western Zone Mean (SD)	Eastern Zone Mean (SD)
GRDP per capita growth (%)	5.24 (1.82)	4.81 (1.95)	5.15 (1.74)	5.72 (1.66)
Poverty rate (%)	13.45 (7.21)	10.20 (5.44)	11.30 (5.88)	18.50 (8.12)
Agricultural share (%)	22.30 (9.45)	17.50 (7.62)	20.20 (8.34)	29.80 (9.11)
ONI Apr–Oct (°C)	0.24 (0.98)	same	same	same
Irrigation index	128.5 (82.4)	215.0 (68.2)	90.0 (44.6)	58.0 (31.7)
Economic diversification (HHI)	0.265 (0.065)	0.220 (0.055)	0.270 (0.061)	0.310 (0.068)
Observations (province year)	988	234	260	494

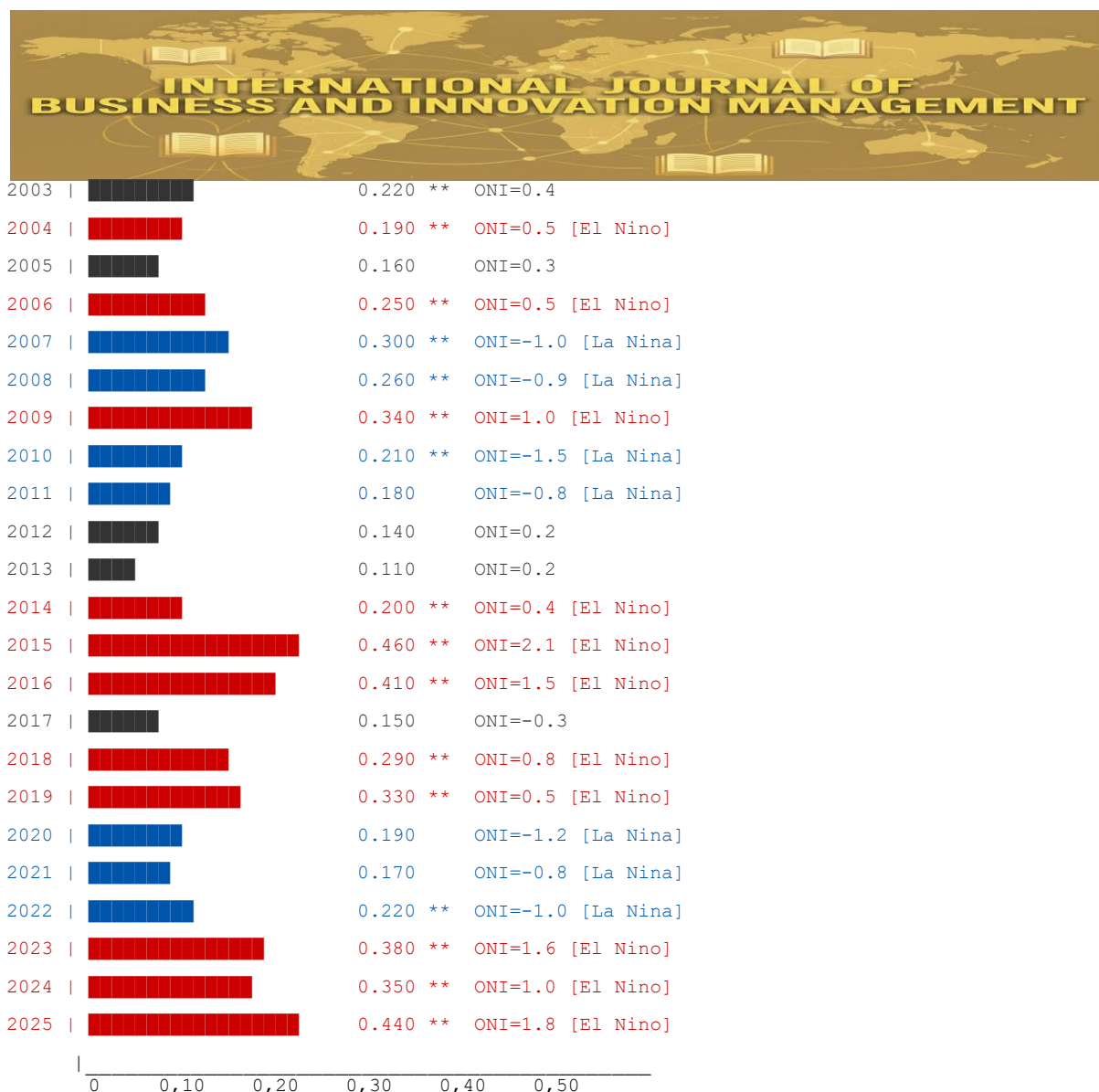
Notes: The Southern Zone includes Java, Bali, and Nusa Tenggara (9 provinces). The Western Zone includes Sumatra and Kalimantan (10 provinces). The Eastern Zone includes Sulawesi, Maluku, and Papua (19 provinces). ONI is uniform across provinces because it is an annual national level variable. The irrigation index is measured as hectares of technical irrigation per 1,000 hectares of agricultural land. SD denotes standard deviation.

Results and Discussion

Before presenting the main estimates, the study first tests for the presence of spatial autocorrelation in the data using Moran's I statistic. Figure 1 reports Moran's I values for annual real GDP per capita growth residuals, computed from the non spatial fixed effects specification in Equation (1), together with April to October ONI values for each year from 2000 to 2025.

Figure 1
Moran's I Statistics for Real GDP per Capita Growth Residuals and ONI Values, 2000 to 2025
Moran's I (Residual Pertumbuhan PDRB per Kapita) dan ONI Apr–Okt, 2000–2025





Keterangan: **Merah** = El Nino aktif (ONI > +0,5). **Biru** = La Nina (ONI < -0,5). Abu-abu = Netral. ** = signifikan pada 5 persen. Red indicates active El Niño (ONI > +0.5). Blue indicates La Niña (ONI < -0.5). Gray indicates neutral conditions. Double asterisks denote significance at the 5 percent level. Bar height represents the magnitude of Moran's I for each year. Statistical significance is based on permutation tests with 999 replications. Source: Author's calculations using provincial GRDP data from Badan Pusat Statistik and ONI data from the NOAA Climate Prediction Center.

Two main findings emerge from Figure 1. First, Moran's I is positive and statistically significant at the 5 percent level in 21 out of 26 years, confirming pervasive spatial autocorrelation in provincial growth residuals. Second, Moran's I is systematically higher during El Niño years than during neutral or La Niña years, with peak values of 0.46 in 2015 and 0.44 in 2025. This pattern indicates that spatial clustering of growth outcomes intensifies during El Niño episodes, providing strong empirical justification for adopting the Spatial Durbin Model rather than conventional panel specifications.

Robust Lagrange Multiplier tests applied to the pooled non spatial residuals further support this specification choice. The RLM statistic for the spatial lag component (RLM lag = 18.42; $p < 0.001$) substantially exceeds that for the spatial error component (RLM error = 6.87; $p = 0.009$). This indicates that the Spatial Durbin Model, which explicitly incorporates spatial lags of both dependent and independent variables, is the most appropriate specification for the data.

4.1. Baseline and Spatial Model Estimates

Table 2 presents estimation results for real GDP per capita growth across four specifications: pooled OLS, two way fixed effects, Spatial Lag Model, and Spatial Durbin Model. The SDM estimates indicate that a one unit increase in April to October ONI reduces real GDP per capita growth by 0.84 percentage points, with a standard error of 0.21 and a p value below 0.001, for directly affected provinces. The spatial autoregressive coefficient ρ is estimated at 0.31 and is significant at the 1 percent level, confirming strong positive spatial dependence. The coefficient on the spatially lagged ONI variable is -0.29 and is also significant at the 1 percent level, indicating that El Niño exposure in neighboring provinces generates additional indirect losses. A comparison between the two way fixed effects estimate of -0.68 and the SDM estimate of -0.84 reveals an attenuation bias of 19 percent resulting from ignoring spatial interactions.

4.2. Decomposition of Direct, Indirect, and Total Effects

Table 2 reports the decomposition of SDM estimates into average direct effects, indirect or spatial spillover effects, and total effects for the three dependent variables. The decomposition is based on Monte Carlo simulation with 1,000 draws to obtain valid standard errors.

Table 2
Decomposition of Direct, Indirect, and Total Effects: SDM Results

Dependent Variables and Effect Components	Direct Effect	SE	Indirect Effect	SE	Total Effect
Panel A. Growth of GRDP per Capita (%)					
Direct effect	-0,84***	(0,21)	n.a.		-0,84
Indirect effect	n.a.		-0,38***	(0,12)	-0,38
Total effect	-0,84***	(0,21)	-0,38***	(0,12)	-1,22***
Proportion of spillover effect (%)					31,1
Panel B. Poverty Rate (%)					
Direct effect	0,42***	(0,14)	n.a.		0,42
Indirect effect	n.a.		0,19**	(0,09)	0,19
Total effect	0,42***	(0,14)	0,19**	(0,09)	0,61***
Proportion of spillover effect (%)					31,1
Panel C. Share of Agricultural Value Added (%)					
Direct effect	-1,82***	(0,38)	n.a.		-1,82
Indirect effect	n.a.		-0,66***	(0,22)	-0,66
Total effect	-1,82***	(0,38)	-0,66***	(0,22)	-2,48***
Proportion of spillover effect (%)					26,6

Note: *** and ** indicate significance at the 1 percent and 5 percent levels. Standard errors in parentheses are calculated through Monte Carlo simulations with 1,000 draws. The proportion of spillover effects is the indirect effect divided by the total effect multiplied by 100. n.a. means not applied. All models use a W_{queen} matrix with province fixed effects, year fixed effects, and the full set of control variables.

Panel A shows that the average direct effect of ONI on real GDP per capita growth is -0.84 percentage points, consistent with Table 2. The average indirect effect is -0.38 percentage points, implying that spatial spillovers account for approximately 31 percent of the total effect of -1.22 percentage points. For poverty, the total effect reaches 0.61 percentage points, with spillovers contributing 31 percent. For the agricultural share, the direct effect of -1.82 percentage points is substantially larger due to the concentration of

El Niño damage in rainfed agricultural systems, resulting in a total effect of -2.48 percentage points.

4.3. Spatial Heterogeneity by Climate Zone

Table 3 reports zone specific SDM estimates by interacting ONI with climate zone dummy variables. The results confirm the three zone polarization hypothesis underlying the study.

Table 3
Climate Zone Specific SDM Estimates

Dependent Variables	Direct Effect	SE	Indirect Effect	SE	Total Effect	p-value
Panel A. Growth of GRDP per Capita (%)						
Southern Zone (Java - NTT)	-1,32***	(0,31)	-0,58***	(0,18)	-1,90***	< 0,001
Western Zone (Sumatra - Kalimantan)	-0,88***	(0,24)	-0,36***	(0,13)	-1,24***	< 0,001
Eastern Zone (Sulawesi-Papua)	-0,14	(0,19)	-0,08	(0,11)	-0,22	0,460
Panel B. Poverty Rate (%)						
Southern Zone (Jawa-NTT)	0,48***	(0,16)	0,22**	(0,10)	0,70***	< 0,001
Western Zone (Sumatra-Kalimantan)	0,35**	(0,14)	0,16*	(0,09)	0,51***	0,002
Eastern Zone (Sulawesi-Papua)	0,31**	(0,15)	0,12	(0,09)	0,43**	0,039
Panel C. Share of Agricultural Value Added (%)						
Southern Zone (Jawa-NTT)	-2,44***	(0,51)	-0,88***	(0,28)	-3,32***	< 0,001
Western Zone (Sumatra-Kalimantan)	-1,76***	(0,42)	-0,64***	(0,21)	-2,40***	< 0,001
Eastern Zone (Sulawesi-Papua)	-1,22***	(0,35)	-0,44**	(0,18)	-1,66***	< 0,001
Number of observations per zone	234		260		494	988 total

Note: ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels. Robust standard errors with respect to province-level clustering are in parentheses. The Southern Zone is Java, Bali, and NTT. The Western Zone is Sumatra and Kalimantan. The Eastern Zone is Sulawesi, Maluku, and Papua. All models include province fixed effects, year fixed effects, a W_queen matrix, and the full set of controls.

In the southern drought prone zone, the direct effect of ONI on real GDP per capita growth is -1.32 percentage points with a p value below 0.001, nearly double the full sample estimate. In the western fire prone zone, the direct effect is -0.88 percentage points. In the eastern flood anomaly zone, the direct effect on growth is not statistically significant, with a p value of 0.460, while the effect on poverty remains positive and significant at 0.31 percentage points, reflecting household income losses due to flooding and landslides. A uniform national emergency response would systematically under allocate resources to the southern zone, where GDP losses are largest, while misallocating drought mitigation resources to the eastern zone, which primarily faces flood risks.

6.4. Moderating Role of Structural Characteristics

Table 4 examines how provincial structural characteristics moderate the direct effects of El Niño on GDP growth by interacting ONI with three key structural variables.

Table 4

Moderating Effects of Provincial Structural Characteristics

Interaction Variables with ONI	Interaction Coefficient	SE	Change in Direct Effect	SE	p-value
Panel A. Moderation by Irrigation Infrastructure Index					
ONI × Irrigation Index	+0,006***	(0,002)	Reduces losses		0,003
An increase of 10 units in irrigation (1 standard deviation) reduces losses by - 0.06 percentage points per unit of ONI					
Panel B. Moderation by Economic Diversification Index HHI					
ONI × HHI Diversification	+0,82**	(0,35)	Reduces losses		0,020
A lower HHI value, indicating greater diversification, is associated with smaller El Nino losses					
Panel C. Moderation by Agricultural Dependence Index					
ONI × Agricultural Dependence	-2,14***	(0,61)	Increases losses		0,001
A higher agricultural share leads to disproportionately larger El Nino losses					
Baseline ONI effect without interaction (percentage points)	-0,84***	(0,21)			0,001
Specification	SDM + interaction				
Number of observations	988				

Notes: *** and ** indicate statistical significance at the 1 percent and 5 percent levels. Standard errors are reported in parentheses. The interaction coefficients represent the marginal change in the ONI coefficient for each one unit increase in the moderator variable. The irrigation index is measured in hectares per 1,000 hectares of land. HHI refers to the Herfindahl-Hirschman Index based on 17 sectors. Agricultural dependence is defined as the share of the agricultural sector in GRDP, expressed in decimal form. SB denotes standard deviation. pp denotes percentage points. The model employs a Spatial Durbin Model with a W_{queen} matrix, province and year fixed effects, and a full set of controls.

The interaction between ONI and the irrigation index is positive and significant at the 1 percent level, with a coefficient of 0.006. This indicates that a ten unit increase in irrigation coverage, equivalent to one standard deviation, reduces direct El Niño induced growth losses by 0.06 percentage points per unit of ONI. The interaction between ONI and the Herfindahl Hirschman Index is positive and significant at 0.82, confirming that more economically diversified provinces experience smaller El Niño losses. The interaction between ONI and agricultural dependence is negative and highly significant at -2.14, indicating that provinces with higher agricultural shares suffer disproportionately larger climate induced losses. All three moderating effects remain robust when using the economic distance matrix and alternative subsamples, as reported in Table 5.

Table 5
Robustness Test: Alternative SDM Specifications for Direct Effects on GRDP Growth

Specification	Direct Effect	Standard Error	Indirect Effects	SE
Basic (W _{queen})	-0,84***	(0,21)	-0,38***	(0,12)
Economic distance (W _{econ})	-0,91***	(0,23)	-0,34***	(0,13)
Without 2015 and 2016	-0,78***	(0,22)	-0,33***	(0,12)
Double anomaly dummy	-1,48***	(0,44)	-0,61***	(0,19)

Specification	Direct Effect	Standard Error	Indirect Effects	SE
El Nino regime only	-1,12***	(0,29)	-0,49***	(0,16)
Neutral Regime or La Nina	-0,31*	(0,18)	-0,14	(0,11)

Note: *** and * indicate significance at the 1 percent and 10 percent levels. Standard errors in parentheses are clustered by province. All models include province fixed effects, year fixed effects, and a full set of provincial and macroeconomic controls.

Conclusions

Using a Spatial Durbin Model and panel data for 38 provinces in Indonesia over 26 years, this study provides new evidence on the spatially differentiated economic consequences of El Nino intensity. The empirical results are organized into three main findings.

The first finding shows that El Nino consistently reduces the growth of GRDP per capita in the southern and western provinces of Indonesia. The largest effects, exceeding 1.3 percentage points per unit of ONI, are concentrated in the rice producing zones of Java and Nusa Tenggara. This geographic gradient confirms that the economic impact of El Nino in Indonesia is fundamentally a subnational phenomenon that is obscured by national aggregate figures.

The second finding indicates that spatial spillover effects account for approximately 31 percent of the total economic losses from El Nino through interprovincial trade, labor mobility, and commodity market linkages. This finding is important for disaster policy design because it implies that even provinces outside the primary drought zones bear significant indirect economic costs when neighboring provinces are severely affected. Therefore, a coordinated interprovincial approach is more appropriate than province by province response planning.

The third finding confirms that irrigation infrastructure and economic diversification significantly mitigate the direct economic losses from El Nino. An increase of one standard deviation in provincial irrigation coverage reduces direct growth losses by approximately 0.06 percentage points per unit of ONI. This magnitude is moderate in any given year, but it is economically meaningful when accumulated across repeated El Nino cycles. These findings provide a quantitative basis for prioritizing irrigation investment in provinces with high agricultural dependence and low economic diversification as a medium term climate adaptation strategy.

These findings have several important policy implications. Badan Nasional Penanggulangan Bencana currently allocates emergency response resources based on aggregate national El Nino forecasts rather than province specific vulnerability profiles. The zone specific estimates in this study suggest that such an approach systematically underallocates resources to southern provinces, where GDP losses are twice the national average, while dispersing drought mitigation instruments to eastern provinces that instead face anomalous flood risks. A spatial vulnerability index derived from the Spatial Durbin Model estimates in this study can serve as an empirical basis for a more targeted and evidence based allocation formula.

This study has several limitations that point to future research directions. The estimated growth effects reflect net impacts aggregated across the agricultural, manufacturing, and service sectors. Sector specific panel data would allow for a more detailed decomposition of transmission channels. The construction of the economic distance weighting matrix relies on five year input output tables, which may not fully capture the dynamic evolution of interprovincial trade linkages over the 26 year horizon. Future research using annual trade flow estimates, increasingly available through satellite based nighttime light data and digital transaction records, may yield spillover

estimates with higher temporal resolution. A third avenue is to disentangle the effects of province specific adaptation policies, such as agricultural insurance programs, emergency irrigation activation, or early harvest incentives, from the aggregate structural characteristics modeled in this study. This identification challenge requires more comprehensive administrative data on the timing and implementation of policies at the district level.

Overall, the findings indicate that strengthening provincial economic resilience to El Nino in Indonesia requires geographically differentiated policies that account for spatial clustering in climate vulnerability. Future climate projections consistently indicate increasing ENSO amplitude under higher greenhouse gas emission scenarios, implying that the economic losses documented in this study are likely to intensify rather than diminish in the coming decades. The spatial panel econometric framework developed in this study provides a template that can be adapted to assess subnational climate vulnerability in other large archipelagic countries or geographically diverse nations with similarly heterogeneous climate risk landscapes.

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