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Does Climate Change Influence Convergence in Indonesia? Spatial Approach

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ABSTRACT

This study examines the nexus between climate change and regional economic convergence in Indonesia using panel data from 34 provinces (2011-2024). Employing the Spatial Durbin Model (SDM), the analysis explicitly captures spatial spillovers across regions. Results confirm conditional β-convergence with a relatively slow rate of 1.02% per year. Climate variables are critical: temperature and precipitation both exhibit inverted U-shaped relationships with growth, indicating that moderate levels support development while extremes become detrimental. Spatial spillovers reveal that severe weather shocks in neighbouring provinces significantly hinder convergence in the region of origin. Conversely, investment shows strong direct and indirect positive effects, while population growth slows convergence, and human capital contributes modestly. Overall, the findings highlight that climate dynamics shape not only local growth trajectories but also interregional interdependencies. The study provides new evidence for developing economies and offers policy insights for inclusive, low-carbon, and climate-resilient regional development.

Keywords: Spatial Econometrics, β-convergence, Climate Change, Regional Growth, Indonesia
JEL Classification: O47, Q54, R11, C33

1. INTRODUCTION

The past few decades have witnessed dramatic shifts in climate and global warming (NOAA, 2023; WMO, 2023). At the global level, the framework linking economic growth and climate change has already been embedded in the 2030 Sustainable Development Goals, particularly Goals 8 and 13. The most significant impacts of climate change include rising sea levels, extreme weather events, altered rainfall patterns, and ecosystem degradation, all of which threaten food security, natural resources, and economic stability. Climate change has therefore become a tangible threat to human well-being, making it a pressing topic among researchers and policymakers alike. The economic growth–climate change nexus has drawn particular attention for two key reasons (Benhamed et al., 2023; Khaliq et al., 2025). First, economic growth is one of the most reliable indicators of overall economic welfare. Second, the availability of relatively long time series data on growth has motivated scholars to focus on the implications of climate change for economic development, especially given its long-term and persistent nature.

Empirical studies on the impact of climate change on economic performance, particularly economic growth, have continued to expand in recent years. Several notable findings from international research include Benhamed et al. (2023); Chamma (2024); Francis et al. (2024); Henseler and Schumacher (2019); Khan and Rashid (2022); Khoualfia and Bardi (2024), while evidence from Indonesia is provided by Khaliq et al. (2025). These studies collectively examine the extent to which climate change constrains economic growth. Colacito et al. (2019) demonstrate that temperature variation affects aggregate outcomes primarily at the sectoral level. Khan and Rashid (2022) find that persistent deviations in temperature—either above or below the initial baseline—are detrimental to real per capita GDP growth. Similarly, Henseler and Schumacher (2019) show that rising temperatures exert a more pronounced negative impact on economic variables in low-income countries compared to high-income ones. By contrast, Sequeira et al. (2018) suggest that temperature fluctuations generally have no significant effects on short- or long-term growth. Finally, Hernandez and Madeira (2022) provide evidence that while changes in rainfall do not significantly influence GDP, higher summer temperatures adversely affect agriculture and fisheries.

In line with these environmental challenges, the growth economics literature has long paid attention to the issue of regional convergence—namely, whether relatively poorer regions grow faster than richer ones, thereby reducing disparities over time (Barro and Sala-i-Martin, 1992; Rey and Montouri, 1999). More recent advances in spatial econometrics highlight the importance of spatial dependence: regional growth is not isolated, but somewhat shaped by technological spillovers, trade linkages, and geographical proximity (Ertur and Koch, 2007). Empirical studies in Indonesia reveal the presence of spatial clustering and convergence clubs among provinces and districts, indicating that regional dynamics cannot be fully understood without accounting for spatial interdependence (Hidayat et al., 2022; 2023; Miranti and Mendez, 2023; Santos-Marquez et al., 2022).

Indonesia's economic growth trajectory over the past decade provides an important empirical context. Between 2011 and 2019, the national economy expanded at a relatively stable pace of 5-6% annually, supported by domestic demand and commodity exports. The COVID-19 pandemic in 2020 triggered a sharp contraction of −2.07%, followed by a rebound of 3.70% in 2021, 5.31% in 2022, and 5.05% in 2023. Although the aggregate recovery appears robust, its distribution has been uneven: regions dependent on tourism or natural resources were more severely affected, while others recovered more quickly. This heterogeneity raises a critical question: Does the national growth trend genuinely foster convergence, or does it instead widen interregional divergence?

In this context, the interaction between climate change and the process of economic convergence emerges as a critical research agenda. Climate risks influence growth through multiple channels: (i) productivity shocks in climate-sensitive sectors such as agriculture and fisheries; (ii) infrastructure damage caused by floods, droughts, and coastal intrusion; and (iii) transition risks stemming from structural shifts in energy and carbon-intensive industries. These impacts are not spatially uniform—provinces differ in terms of exposure, adaptive capacity, and sectoral structure—thus potentially reshaping both the speed and pattern of convergence. Moreover, the presence of spatial spillovers implies that climate shocks in one region can affect neighbouring regions, either reinforcing or undermining convergence dynamics.

Despite the rapidly expanding literature on the economic impacts of climate change, most studies remain concentrated at the global or cross-country level, with limited attention to the subnational dynamics of growth and inequality. In the Indonesian context, previous research on regional convergence has primarily employed classical or spatial econometric frameworks that omit climate-related variables, thereby overlooking the heterogeneous ways in which climate risks influence regional growth trajectories. This leaves a significant empirical void, given that provinces differ substantially in terms of climate exposure, adaptive capacity, and sectoral composition. Moreover, existing spatial convergence studies emphasize spillover effects and geographic interdependencies, but little is known about how these spatial linkages interact with asymmetric climate shocks across regions.

Addressing this gap, the present study offers a novel contribution by explicitly integrating climate indicators—such as temperature anomalies and rainfall variability—into the spatial econometric framework of β-convergence. This approach seeks to provide a more comprehensive understanding of whether climate change accelerates or, conversely, slows down the process of regional economic convergence in Indonesia. The findings are expected not only to enrich theoretical debates on the nexus between climate change and regional growth dynamics but also to deliver important policy implications for designing inclusive and equitable strategies toward low-carbon and climate-resilient development.

The remainder of this paper is organized as follows. The section on Literature Review and Data and Methods discusses previous studies on convergence in Indonesia and outlines the methodological framework and data employed in this research. The Results section presents the main findings, both from the perspective of the classical convergence framework and from an extended model that incorporates climate change variables. Finally, the Conclusion section summarizes the key insights, highlights potential avenues for future research, and elaborates on the policy implications for fostering climate-resilient and inclusive economic development in Indonesia.

2. LITERATURE REVIEW

The concept of economic convergence has been a central theme in the growth literature, particularly within the framework of the neoclassical Solow–Swan model. This model posits that economies with lower initial income levels tend to grow faster than wealthier economies, thereby fostering a long-run tendency toward convergence (Barro and Sala-i-Martin, 1992). Sala-i-Martin (1996) distinguishes between two forms of convergence: β-convergence, which occurs when poorer regions grow more rapidly than richer ones, and σ-convergence, which reflects a decline in income dispersion across regions over time. He argues that β-convergence is a necessary condition for σ-convergence, although it does not guarantee its occurrence. Within this framework, the literature also distinguishes between absolute convergence, where all economies converge toward the same steady state, and conditional convergence, which only materializes once structural characteristics such as savings rates, population growth, and technology are taken into account. Nevertheless, empirical evidence often reveals divergence rather than convergence, giving rise to the notion of convergence clubs, in which groups of regions with similar characteristics converge among themselves but not with others (Quah, 1996).

Spatial economics refines this understanding by emphasizing the role of geography and interregional linkages (Capello and Nijkamp, 2009; Nijkamp and Poot, 1998). Regional growth trajectories are not independent; instead, they are shaped by spatial spillovers, technological diffusion, migration, and trade interconnections (Rey and Montouri, 1999). Spatial econometrics provides the methodological tools to capture such interdependencies and has become increasingly employed in the study of regional convergence. Moreover, climate–economy interactions have emerged as a critical dimension of growth dynamics. Climate change impacts economic outcomes through various channels, including agricultural productivity, labor productivity, infrastructure resilience, and health costs (IPCC, 2022). These impacts are highly uneven across regions, raising the question of whether climate change exacerbates or mitigates existing regional disparities.

The nexus between climate change and economic growth has generated substantial scholarly debate, with empirical evidence pointing to both detrimental and heterogeneous effects across regions and over time. A growing strand of research highlights that climate shocks—particularly rising temperatures and extreme weather events—tend to suppress economic growth by reducing labor productivity, disrupting agricultural and industrial outputs, and accelerating capital depreciation (Duan et al., 2022; Khan and Rashid, 2022; Khurshid et al., 2022). For example, Baarsch et al. (2020) document that climate change undermines income convergence in Africa, thereby exacerbating persistent inequalities under warming scenarios. Likewise, Chamma (2024) and Rais and Tahtane (2022) find that climatic variability severely constrains both aggregate and sectoral growth in Sub-Saharan Africa, while Francis et al. (2024) stress that developing economies remain disproportionately vulnerable to climate-related disruptions. In contrast, more recent studies underscore spatial heterogeneity and conditional effects, arguing that the magnitude and direction of climate impacts depend on institutional quality, adaptive capacity, and sectoral structures (Adom and Amoani, 2021; Chandio et al., 2022; Kumar and Maiti, 2024). For instance, Chen et al. (2023) show that urban total factor productivity in China responds differently to climate dynamics compared with rural areas, whereas Khoualfia and Bardi (2024), using a Panel ARDL framework, reveal mixed outcomes across European economies.

Extending this debate, an emerging body of literature employs spatial econometric methods to capture the geographically interdependent nature of climate–economy linkages. Spatial approaches reveal that climate shocks are not confined within administrative boundaries but rather exhibit significant spillover effects across regions. Benhamed et al. (2023) demonstrate, through their studies, that temperature anomalies and precipitation shocks exert both direct and spatially lagged effects on regional economic performance, underscoring the need to account for spatial dependence in growth models. Similarly, Khaliq et al. (2025) employ spatial Durbin models to demonstrate that climate variability in one province of Indonesia has a significant impact on the economic outcomes of neighbouring provinces, highlighting the existence of cross-border externalities.

The linkage between climate change and economic convergence remains a contested terrain in recent literature, revealing complex and sometimes contradictory patterns across regions. Baarsch et al. (2020) provide evidence that climate change undermines income convergence in African countries, suggesting that warming scenarios perpetuate inequality among vulnerable economies. This view is shared by Chamma (2024) and Rais and Tahtane (2022), who report that both aggregate and sectoral growth in Sub-Saharan Africa are sharply constrained by climatic variability. However, these predominantly negative findings are tempered by studies such as those by Adom and Amoani (2021), who emphasize that institutional readiness and adaptation capacity can moderate the effects of climate-related shocks on convergence trajectories. Similarly, Kumar and Maiti (2024) and Chandio et al. (2022) identify context-specific conditional factors—such as resilient infrastructure, human capital, and economic diversification—that may either attenuate or exacerbate convergence outcomes under climate stress. Overall, the heterogeneous results underscore that evidence of climate-driven divergence or convergence depends on regional climate exposure, adaptive capacity, and structural conditions, highlighting the need for spatially disaggregated, region-specific analyses rather than relying on aggregate trends.

Recent empirical studies increasingly adopt spatial econometric techniques to examine the nexus between climate change and conditional economic convergence, highlighting how climate-induced shocks not only shape growth trajectories but also condition the speed and direction of regional convergence. Benhamed et al. (2023) provide evidence that temperature anomalies and precipitation variability exert both direct and spatially lagged effects on regional output, thereby influencing the extent to which economies converge under heterogeneous climatic pressures. Similarly, Khoualfia and Bardi (2024) apply a spatial panel ARDL framework to European economies, revealing that climate variability significantly alters convergence dynamics. Some countries experience slowdowns in convergence due to climate stress, while others maintain conditional convergence through institutional adaptation. Baarsch et al. (2020) employ a Spatial Durbin SAR framework and demonstrate that rising temperatures significantly depress per capita income growth, both directly and through spatial spillover effects, across low-income African economies, thereby slowing convergence trajectories.

Li and Song (2022) employed a spatial β-convergence model to investigate green development in China, revealing evidence of both absolute and conditional spatial convergence, where green innovation accelerated the pace of territorial improvement. Another study by Zhang et al. (2022), which analyzed agricultural eco-efficiency, also revealed spatial autocorrelation patterns (high-high and low-low clustering) and a catching-up effect in lagging provinces, thereby determining the pace of regional convergence. Collectively, these studies demonstrate that climate change not only alters growth trajectories in isolation but also interacts with regional heterogeneity and spatial connectivity, making it an important determinant of convergence outcomes in both developing and emerging economies.

3. METHODOLOGY

The dataset employed in this study is a panel dataset, combining cross-sectional and time-series dimensions. The unit of analysis consists of 34 provinces in Indonesia. The time series covers the period 2011-2024, yielding a total of 14 years and 476 observations. The primary data sources are various government institutions, most notably Statistics Indonesia (BPS). In addition, spatial data are supported by shapefiles (.shp) of Indonesia, categorized by provincial administrative boundaries.

The theoretical foundation underpinning this study's conceptual framework is the spatial MRW model developed by Fischer (2011). It is assumed that each province follows a Cobb–Douglas production function, specified as follows:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} H_{it}^{\alpha_H} L_{it}^{1-\alpha_K-\alpha_H} \tag{1}$$

Here, Y denotes output, K physical capital, H human capital, L labor, and A the level of technological knowledge. The exponents α_K and α_H represent the output elasticities of physical and human capital, respectively. Following Mankiw et al. (1992), it is assumed that $\alpha_K>0$, $\alpha_H>0$ and $\alpha_K + \alpha_H<1$, which implies diminishing returns to capital.

Referring to Ertur and Koch (2007), the study models A_{it} as follows:

$$A_{it} = \Omega_t k_{it}^{\phi_K} h_{it}^{\phi_H} \prod_{j=1}^{n} A_{jt}^{\gamma w_{it}} \tag{2}$$

The development of output per worker in region i is governed by the dynamic equations for k, h, and cc given by:

$$\dot{k}_{it} = s_i^K y_{it} - (\delta + n_i) k_{it} \tag{3a}$$

$$\dot{h}_{it} = s_i^H y_{it} - (\delta + n_i) h_{it} \tag{3b}$$

$$cc_{it} = s_i^{cc} y_{it} - (\delta + n_i) cc_{it} \tag{3c}$$

3.1. Spatial Durbin Model (SDM)

The Spatial Durbin Model (SDM) can be viewed as an extension of the Spatial Autoregressive Model (SAR) or spatial lag specification, in which spatially lagged independent variables are incorporated alongside the spatial lag of the dependent variable. In other words, the SDM not only accounts for spatial dependence in the outcome variable but also explicitly captures spatial spillovers transmitted through the explanatory variables. This dual weighting approach enhances the model's ability to disentangle direct effects operating within a region and indirect effects originating from neighboring regions (Elhorst, 2014; Elhorst and Emili, 2022; Murialti et al., 2025).

Formally, the Spatial Durbin Model can be expressed as follows:

$$Y = \rho W_1 Y + \beta_0 + X\beta_1 + W_1 X \beta_2 + \varepsilon, \varepsilon \sim N\left(0, \sigma^2 I\right) \tag{4}$$

Estimation of SDM parameters using Maximum Likelihood Estimation, with the following equation:

$$Y = \rho W_1 Y + \beta_0 + X\beta_1 + W_1 X \beta_2 + \varepsilon \tag{5}$$

Estimation β adalah:

$$\hat{\beta} = \left(Z^T Z\right)^{-1} Z^T \left(I - \rho W_1\right) y \text{, dengan } Z = \left[I\, X\, W_1\, X\right]$$

In spatial analysis, the spatial weights matrix is used to capture the closeness between regions on the premise that geographically nearer areas exert greater influence than more distant ones (Anselin, 1995). In this study, a spatial weights matrix based on Euclidean distance is applied because the provinces under investigation are not confined to land boundaries alone but are also separated by rivers and seas; moreover, a distance-based approach supports measuring proximity between provincial capitals. The spatial weights matrix ***W*** is constructed using the Euclidean distances between coordinate points (X, Y) that represent neighborhood relations or closeness between regions (Dattorro, 2015). To ensure comparability and interpretability, the weights were row-standardized such that the elements of each row sum to one. A distance threshold was applied to avoid excessive sparsity in the matrix, thereby retaining only the nearest neighboring provinces. In this study, the spatial weights were computed with GeoDa, and spatial panel calculations were performed in Stata using the spwmatrix command (Jeanty, 2010) and xsmle (Belotti et al., 2017).

The spatial convergence modeling employed in this study draws on the frameworks developed by Aspiansyah and Damayanti (2019); Fischer (2011); Hidayat et al. (2023), and is further adapted to the present context by explicitly focusing on spillover effects from rising temperatures and precipitation in neighboring provinces. Accordingly, the specification of the Spatial Durbin Model is formulated as follows:

$$\begin{aligned} \Delta \ln y_{it} = {} & \beta_0 - \beta_1 \ln y_{it-1} + \beta_2 T_{it} + \beta_3 T_{it}^x + \beta_4 P_{it} + \beta_5 P_{it}^x \\ & + \beta_6 \ln k_{it-1} + \beta_7 HC_{it} + \beta_8 \ln(n + g + \delta) \\ & + \rho_0 \sum_{j=1}^{N} w_{ij} \Delta \ln y_{jt} + \rho_1 \sum_{j=1}^{N} w_{ij} T_{jt}^x + \rho_2 \sum_{j=1}^{N} w_{ij} P_{jt}^x + \varepsilon_{it} \end{aligned} \tag{6}$$

Where w_{ij} denotes the elements of the spatial weight matrix that capture spatial connectivity; ρ_o is the coefficient associated with economic growth in neighboring provinces; ρ_1 measures the spillover effect of temperature increases in neighboring regions; ρ_2 captures the spillover effect of precipitation changes in neighboring regions; and ε_{it} is a random shock term.

The operational definitions of control variables are presented in Table 1. The use of exponents in the temperature and precipitation variables is intended to capture potential non-linear effects, particularly an "inverted U-shaped" relationship, which suggests that the association between these variables and economic growth is neither proportional nor strictly monotonic. Specifically, an exponent of 1.2 is applied under the assumption that moderate

Table 1: Research variable and operational definitions

No.	Variable	Operational definition	Measurement
1.	GRDP per capita $Y_{i,t}$	The per capita Gross Regional Domestic Product (GRDP) of province *i* in year *t*, measured at constant 2010 prices. The use of per capita output as the leading indicator follows the convergence framework proposed by Barro and Sala-i-Martin (1992)	Million Rupiah
2.	Initial income $Y_{i,t-1}$	This variable refers to the level of per capita GRDP of province *i* in the previous year (*t–1*), measured at constant 2010 prices. Following the convergence hypothesis introduced by Barro and Sala-i-Martin (1992), initial income serves as a benchmark to examine whether poorer regions tend to grow faster than richer ones. In this context, the variable not only reflects economic starting points but also embodies the dynamics of catching-up or divergence across provinces.	Million Rupiah
3.	Temperatur (*T*)	Annual average temperature issued by BMKG and BPS publications	Celcius
4.	Precipitation (*P*)	Number of rainy days in a year published by BPS	Days
5.	Investment ($k_{i,t-1}$)	Investment is proxied by Gross Fixed Capital Formation (GFCF). In this study, investment is represented using its one-period lag (lag-1), reflecting the idea that the effect of capital accumulation on economic growth does not occur instantaneously but with some delay. This approach is consistent with the findings of Hidayat et al. (2023), who emphasize the role of lagged investment in shaping regional growth dynamics.	Million Rupiah
6.	Human Capital ($HC_{i,t}$)	Human capital in this study is defined as educational investment, proxied by the Net Enrollment Rate (NER) at the senior high school (SMA/equivalent) level. This measure reflects the proportion of the relevant age group who are actually enrolled in senior secondary education. The use of senior high school education as a proxy is consistent with the approach of Mankiw et al. (1992), who employ secondary school attainment as a standard indicator of human capital in growth models.	Percent
7.	Population growth (n_{it})	Population growth is measured as the annual percentage increase in the total population of province *i* at time *t*. This variable captures demographic dynamics that may influence labor supply, market size, and regional economic performance—published by BPS.	Percent
8.	(g+δ)	This variable represents the combined rate of technological progress and capital depreciation. Following the standard assumption in MRW growth frameworks, it is assumed to be constant and identical across all provinces, with a value of 0.05, as adopted in Mankiw et al. (1992). This assumption allows the focus to remain on differences in saving, investment, and human capital accumulation across regions, rather than on variations in technology or depreciation.	

increases in rainfall and temperature may initially stimulate economic growth (via the term aX), but beyond a certain threshold—determined by $\left(\frac{a}{1.2b}\right)^5$—the adverse effects ($bX^{1.2}$) become dominant, thereby reducing growth.

To examine whether spatial dependence exists in the economic convergence model, we first conduct the heterogeneity test proposed by Pesaran et al. (2001) on a non-spatial panel data specification. If the probability value of the Pesaran test is smaller than 0.05, the null hypothesis of cross-sectional independence is rejected, indicating the presence of spatial dependence; in such a case, the analysis proceeds with a spatial econometric framework.

In the convergence framework, a negative coefficient of β_1 implies convergence, whereas a positive coefficient indicates divergence. The speed of convergence (λ) can be derived from the transformation of the estimated parameter, where:

$$\beta_1 = \frac{1-e^{-\lambda\tau}}{T}, \text{so that } \lambda = \frac{-\ln\left(1+\tau\beta_1\right)}{T}$$

Here, λ captures the rate at which an economy's output approaches its steady state, suggesting that poorer regions are expected to grow faster than richer ones until the steady state is reached (Barro and Sala-i-Martin, 2004). Furthermore, the concept of half-life of convergence (τ*) illustrates the time required for an economy to close half of the gap between its current output level and the steady state. This is given by:

$$e^{-\lambda\tau} = \frac{1}{2}\text{, so that } \tau^* = \frac{\ln 2}{\lambda} \approx \frac{0,69}{\lambda}$$

The half-life provides an intuitive measure of how quickly regional disparities are reduced in practice: the smaller the half-life, the faster the catch-up process among provinces.

4. RESULTS AND DISCUSSION

In the first stage, model selection for the static panel framework was conducted using the Hausman test to determine the most appropriate specification between the fixed effects and random effects models. The decision rule applied is that if the probability value is <0.05, the fixed effects model is preferred; otherwise, the random effects model is selected. As shown in Table 2, the estimated Hausman statistic yields a probability value below the 0.05 threshold, indicating that the fixed effects specification provides a better fit for the data. Subsequently, the Pesaran cross-sectional dependence test was performed to examine whether spatial dependence exists across provinces. The test result shows a probability value smaller than 0.05, implying the presence of significant cross-sectional dependency among the regions under study. This outcome validates the need to proceed with spatial econometric modeling, as economic dynamics across Indonesian provinces cannot be considered in isolation but are instead interconnected through spatial spillovers.

For the selection between fixed and random effects specifications within the Spatial Durbin Model (SDM), the Hausman test was

Table 2: Result model data panel static and spatial

Variable	FEM1 (1)	SDM-FE1 (2)
Y_{t-1}	−0.1568***	−0.1325***
	(0.0488)	(0.0271)
T	0.2157***	0.1474***
	(.0783)	(0.0559)
T^X	−0.0773***	−0.0521***
	(0.0279)	(0.0198)
P	−0.0027***	−0.0018***
	(0.0005)	(0.0003)
P^X	0.0005***	0.0003***
	(0.0001)	(0.00008)
k_{t-1}	0.0907***	0.0910***
	(0.0319)	(0.0155)
(n+g+δ)	−0.6820***	−0.6169***
	(0.1979)	(0.0617)
HC	−0.0004	−0.0006 *
	(0.0009)	(0.0003)
Spatial effect		
ρ	-	0.4972***
		(0.1010)
Wx T^x		−0.0023 **
		(0.0011)
Wx P^x		0.00001
		(0.00001)
Pesaran test (Prob)	0.0000	-
Convergence speed	1.21	1.02
Half-life time (year)	56.89	68.27
Hausman (Prob)	0.0000	0.0000
AIC	−1930.1658	−2023.9557
Log-likelihood	973.0828	1039.9778
R^2	0.2200	0.2165
N	476	476

The spatial model is based on the Euclidean distance matrix. AIC=Akaike information criterion. Heteroskedasticity-robust standard errors are shown in parentheses. *P<0.1, **P<0.05; ***P<0.01

employed. The decision criterion states that if the probability value is <0.05, the fixed effects model is preferred; otherwise, the random effects specification is chosen. As reported in Table 2, the Hausman test yields a probability value of 0.000, confirming that the fixed effects specification is the most appropriate for the SDM. To further assess the suitability of spatial versus non-spatial models, model performance was compared using the Akaike Information Criterion (AIC) and the log-likelihood value. The decision rules applied are that the model with the smaller AIC and the larger log-likelihood is preferred. The results demonstrate that the spatial specification outperforms the non-spatial counterpart, as indicated by a lower AIC and a higher log-likelihood. This finding validates the adoption of the spatial econometric framework for the present study, highlighting the necessity of accounting for spatial interdependencies in the analysis of regional economic convergence in Indonesia.

Based on the results reported in Table 1, the coefficient of the lagged income variable (Yt-1) is negative and statistically significant at −0.1325, indicating the presence of regional economic convergence in Indonesia. The implied speed of convergence is estimated at 1.02% per year, suggesting that regional economies are gradually approaching their steady state. This further implies that poorer provinces tend to grow faster than richer ones. However, the process remains relatively slow—requiring approximately 68.27 years for half of the income gap to be closed.

This finding is consistent with the neoclassical growth theory and contributes to the empirical literature by providing updated evidence on the long-run dynamics of regional convergence in Indonesia. Compared to previous studies, the estimated convergence rate in this study is lower than that reported by Aspiansyah and Damayanti (2019), who found a speed of 1.8% per year with a half-life of 39 years, and lower than Hidayat et al. (2022) at 2.35% and Hidayat et al. (2023) at 4.01% for the case of Sumatra. However, it is higher than the earlier estimate by Aritenang (2014), who reported a convergence rate of 0.6% during the period 1994-2004.

Subsequently, the results of conditional convergence are shaped by the inclusion of control variables. First, temperature is found to exert a positive and statistically significant influence on convergence, with a coefficient of 0.1474 at the 1% level. This indicates that the average annual temperature across regions significantly enhances the speed of convergence. In the context of Indonesia, considerable temperature variation can be observed across regions: some areas exhibit an annual average as low as 21.7°C, typically located in mid-to-highland topographies, while others experience averages as high as 30.04°C, primarily in coastal and mid-lowland areas. Overall, these temperature differences do not appear to generate substantial economic disadvantages at the regional level, suggesting that moderate climatic heterogeneity may instead facilitate adjustment and adaptation dynamics that support convergence.

These findings suggest that moderate temperature variations in the Indonesian context may still support, rather than hinder, the process of economic equalization across regions. Unlike the more extreme manifestations of global climate change—such as prolonged droughts or severe heatwaves—the current range of temperature disparities in Indonesia appears to remain within tolerable limits and does not significantly disrupt regional productivity. On the contrary, such climatic heterogeneity may even foster localized comparative advantages in both agricultural and non-agricultural sectors, depending on the climatic suitability of each province. Nevertheless, it is important to acknowledge that these positive effects may not be sustainable under future scenarios of intensified global warming. Rising temperatures could shift existing thresholds and potentially reverse the current beneficial role of climate in facilitating regional convergence, thereby posing new risks to long-term economic resilience.

Second, the findings provide empirical evidence that climate variability, particularly temperature fluctuations, plays a substantial role in influencing the process of economic convergence. As reported in Table 1, the variable T^X or $T^{1.2}$ produces a statistically significant negative coefficient of -0.0521 at the 1% level. This result suggests that a 1.2-fold increase in the annual average temperature is associated with a slower rate of convergence across regions. In other words, areas exposed to rising temperatures face increasing challenges in narrowing the development gap compared to their counterparts. This outcome is consistent with the broader literature, which emphasizes the adverse effects of climate change on economic performance.

A significant and sustained increase in temperature tends to diminish agricultural productivity, particularly in economies that remain highly dependent on primary sectors such as farming and plantation activities. Prolonged droughts, for example, not only reduce crop yields but may also trigger food insecurity, leading to a scarcity of staple commodities. Consequently, such climate-induced shocks can exacerbate regional disparities, delay structural transformation, and constrain the overall capacity of economies to achieve sustainable growth. Our finding that temperature shocks slow convergence (−0.0521) is consistent with Baarsch et al. (2020) for Africa, but contrasts with Kumar and Maiti (2024), who emphasize adaptation capacity in Asia.

Taken together, these findings underscore the importance of integrating climate resilience into regional development strategies. Without adequate adaptation measures—such as investments in climate-resilient infrastructure, agricultural innovation, and diversification of the economic base—regions highly vulnerable to temperature shocks are likely to experience a prolonged convergence process. This has significant policy implications, highlighting that climate change is not merely an environmental concern but also a central factor shaping long-term economic dynamics.

The subsequent results reveal that rainfall or precipitation, as a climate indicator, significantly impacts regional convergence, with a negative coefficient of −0.0018. This suggests that excessive precipitation undermines the convergence process—a finding that aligns with recent regional studies. For instance, high-resolution modeling of Southeast Asia by (Hariadi et al., 2024) anticipates increased extreme rainfall under warming scenarios, while (Huang et al., 2024) show that exposure to such extreme precipitation disproportionately threatens economic well-being and GDP across vulnerable regions. In Indonesia's predominantly agricultural economy, recurring heavy rainfall disrupts crop cycles, damages infrastructure, and widens interregional disparities. Together with the earlier evidence on temperature, these results underscore a broader pattern in which moderate climatic conditions may sustain economic growth and reduce disparities, but climate extremes—whether in temperature or rainfall—pose significant obstacles to regional equalization.

In contrast to the adverse effects of excess rainfall, the estimation results show that precipitation raised to the exponent of 1.2 yields a positive and statistically significant impact on convergence. This ostensibly paradoxical finding may be explained by Indonesia's diverse topography, which spans coastal plains, lowlands, and highlands. In regions prone to drought—such as East Nusa Tenggara—where rains are often scarce and dry seasons prolonged, even modest increases in rainfall can be transformative, nourishing crops, replenishing water sources, and reducing regional disparities.

In contrast to the negative impacts of excessive rainfall, the estimation results show that precipitation raised to the 1.2 exponent exerts a positive and statistically significant effect on regional convergence. This seemingly paradoxical outcome may be attributed to Indonesia's varied topography—urban lowlands, coastal plains, and highlands—that moderates climate impacts. In drought-prone provinces like East Nusa Tenggara, where dry seasons are harsh and rains are infrequent, even modest increases in rainfall can make a tangible difference in maintaining agricultural productivity and reducing economic disparity. Recent regional studies support this interpretation. For example, Kuswanto et al. (2021) findings underscore that in areas vulnerable to water scarcity, incremental rainfall gains—though modest by aggregate standards—can have substantial positive effects. This observation echoes findings by Ul Moazzam et al. (2022) in Northern Pakistan, where moderate rainfall variability supported agricultural resilience (measured via SPI and drought indices). More recently, (Viana et al., 2025) report in Mato Grosso, Brazil, that seasonal rainfall variability, although not the primary determinant of crop patterns, helped sustain planting schedules in marginal zones—especially when aligned with soil suitability. Together with the inverted U-pattern observed in temperature dynamics, these insights underscore that climate impacts on regional convergence are deeply context-specific: moderate climatic conditions can enable growth in vulnerable regions, whereas extremes—whether heat or downpours—typically undermine it.

The empirical findings reveal that investment exerts a significant influence on the process of regional convergence, with a 1% level of significance and a coefficient value of 0.09 across both spatial and non-spatial models. This result highlights the pivotal role of capital accumulation in driving economic equalization between regions. By employing lagged investment as a proxy, the study demonstrates that the effects of investment are not instantaneous; instead, they materialize over time, reflecting the delayed but enduring contribution of past investment to current economic performance. Such evidence underscores the intertemporal nature of growth, where today's development outcomes are inseparably linked to yesterday's policy and investment decisions.

These findings are consistent with earlier studies, including Hidayat et al. (2022; 2023), which similarly emphasize that sustained investment is a critical determinant of regional growth convergence. Beyond statistical significance, the results carry broader policy implications: stimulating and maintaining investment flows is essential not only for promoting short-term growth but also for securing long-term regional equity. In this sense, investment functions as more than a mere economic variable; it serves as a pathway toward reducing disparities, strengthening resilience, and enabling regions to advance along a sustainable development trajectory collectively.

The results indicate that population growth exerts a significant influence on regional convergence, even when interregional linkages are taken into account. This is reflected in the estimated coefficient of $(n + g + \delta)$, which is −0.6169 and statistically significant at the 1% level (Table 2). The negative sign suggests that higher population growth may place downward pressure on the convergence process by diluting capital accumulation and slowing the pace at which poorer regions can catch up with richer ones. In other words, unchecked demographic expansion risks creating a drag on economic performance, making convergence more challenging to achieve. From a policy perspective, these findings highlight the need for population management strategies as part of broader efforts to sustain growth and convergence. Policymakers are encouraged to implement programs that balance demographic dynamics with economic capacity, such as investments in education, health, and human capital development, alongside family planning initiatives. Without such interventions, the risk of economic stagnation may persist, particularly in regions already facing structural challenges. These results are consistent with previous studies, including Aspiansyah and Damayanti (2019) and Sun et al. (2017), which documented the complex role of population growth in shaping long-term regional economic outcomes.

The analysis further reveals that human capital, proxied by the net enrollment ratio, has a coefficient of −0.0006 and is statistically significant at the 10% level in the spatial model. The negative sign, although relatively small in magnitude, indicates that variations in educational participation may not immediately translate into higher regional convergence. This result suggests that while education is critical for long-term growth, its short-run impact on equalizing economic performance across regions is more nuanced and may be influenced by spatial spillovers or disparities in education quality. Similar outcomes were reported by Ciccone and Papaioannou (2009), who found that differences in schooling levels did not always guarantee faster regional convergence in European regions.

From a policy standpoint, these findings highlight the importance of not only expanding access to education but also improving its quality and relevance to regional economic needs. Investments in human capital should therefore go beyond increasing enrollment figures to include strengthening vocational training, aligning curricula with labor market demand, and ensuring equitable access across regions. Empirical studies such as Barro (2013) and Hanushek and Woessmann (2012) underline that the economic impact of education depends less on the quantity of schooling and more on the cognitive skills and competencies acquired. This implies that in the Indonesian context, policies should focus on enhancing both quality and equity in education to enable human capital to serve as an effective driver of regional convergence.

The spatial effects reported in Table 2 provide compelling evidence that drastic weather changes in neighboring regions hinder convergence in the originating province, with a coefficient of −0.0023 that is statistically significant at the 5% level. This finding reflects the presence of negative spillovers from cross-regional climate shocks, whereby climatic instability in one province can slow growth trajectories and widen convergence gaps in surrounding areas. Interestingly, the results also show that shocks associated with increased precipitation in neighboring provinces do not exert a significant effect on the convergence process of the home region. This suggests that while moderate rainfall fluctuations may be absorbed without significant disruption, more extreme climatic events—such as abrupt temperature shifts or severe weather volatility—play a more decisive role in shaping cross-regional growth dynamics. Finally, beyond the climate dimension, the results indicate that positive spillovers from economic growth in neighboring provinces can accelerate the convergence process of the home region, supporting the notion that spatial interdependencies in economic activity remain a crucial driver of regional equalization.

Beyond climatic factors, significant spatial effects are also observed in the interaction of regional economic activities. Stronger economic performance in neighboring provinces is shown to accelerate the attainment of a steady state in the home region. This finding aligns with growth spillover theory, which emphasizes the role of regional interconnectedness in facilitating the diffusion of economic development (Hidayat et al., 2022; 2023; Lesage and Fischer, 2008).

From a policy perspective, the results underscore the importance of adopting an integrated, region-based development strategy rather than a fragmented, province-by-province approach. Coordinated planning across provinces is essential not only to mitigate climate-related risks but also to harness the potential of economic spillovers as a driver of long-term regional convergence. In this sense, spatial cooperation becomes a cornerstone for promoting more resilient and equitable growth trajectories in Indonesia.

The estimation results of the Spatial Durbin Model (SDM) presented in Table 3 highlight the importance of distinguishing between direct, indirect, and total effects when analyzing the dynamics of regional economic growth in Indonesia. The negative and highly significant coefficient of the lagged dependent variable (Yt-1) across all effects provides robust evidence of conditional convergence, in line with the neoclassical growth framework. In this context, significant direct effects capture the impact that occurs within the region of origin itself, while indirect effects represent the spillover impacts transmitted through neighboring regions. This distinction is crucial for understanding not only how regional characteristics shape their own growth trajectories but also how interregional linkages contribute to the broader process of economic convergence.

Climate-related variables emerge as critical determinants. Temperature (T) exerts a positive and significant direct effect

Table 3: Result: Direct, indirect, total impact from the spatial Durbin model

Variable	Direct (1)	Indirect (2)	Totals (3)
Y_{t-1}	−0.1406***	−0.1375*	−0.2782**
	(0.0328)	(0.0797)	(0.1093)
T	0.1548**	0.1562	0.3111*
	(0.0632)	(0.1151)	(0.1727)
T^X	−0.0550**	−0.0598	−0.1149*
	(0.0225)	(0.0420)	(0.0625)
P	−0.0019***	−0.0018**	−0.0037***
	(0.0004)	(0.0008)	(0.0012)
P^X	0.0003***	0.0004**	0.0007***
	(0.00008)	(0.0001)	(0.0002)
k_{t-1}	0.0969***	0.0921**	0.1891***
	(0.0180)	(0.0464)	(0.0606)
$(n+g+\delta)$	−0.6542***	−0.5952***	−1.2495***
	(0.0538)	(0.2112)	(0.2088)
HC	−0.0006 *	−0.0005*	−0.0011**
	(0.0003)	(0.0003)	(0.0006)

The spatial model is based on the Euclidean distance matrix. Heteroskedasticity robust standard errors are shown in parentheses. *P<0.10, **P<0.05; ***P<0.01

on growth. At the same time, its squared term (T^X) displays a negative coefficient, confirming a non-linear, inverted U-shaped relationship between temperature and economic performance. A similar pattern is observed for precipitation (P) and its squared term (P^X), suggesting that moderate rainfall supports growth. However, excessive levels eventually become harmful, particularly for climate-sensitive sectors such as agriculture and fisheries. Taken together, these results underscore that climate dynamics shape not only local economic performance through direct effects but also broader regional interdependencies through indirect spillovers, thereby collectively influencing the overall trajectory of economic convergence.

Investment, proxied by lagged capital formation, shows a strong positive and statistically significant effect on convergence, both directly and indirectly. This finding underscores the central role of sustained capital accumulation in reducing regional disparities, both from the region of origin and from neighboring regions. Conversely, population growth ($n+g+\delta$) exerts a negative and highly significant effect, indicating that rapid demographic expansion dilutes capital per worker and hinders the pace of convergence. Interestingly, human capital (HC), proxied by secondary school enrollment, yields a small but statistically significant negative coefficient. This result suggests that the contribution of education to convergence may be delayed, potentially reflecting issues of quality, mismatch with labor market needs, or the time required for human capital investments to translate into measurable productivity gains.

5. CONCLUSION

This study confirms the existence of conditional regional economic convergence in Indonesia, shaped by the interplay of climate, investment, demographics, and spatial interdependencies. Climate variables exhibit a non-linear relationship: moderate levels of temperature and precipitation foster growth, while excessive levels hinder convergence. Notably, when precipitation is modeled with an exponent of 1.2, the results turn positive and significant, highlighting the heterogeneous benefits of rainfall in drought-prone regions such as East Nusa Tenggara, where even modest increases in precipitation can support agriculture and reduce disparities. Investment emerges as a critical driver of convergence, whereas rapid population growth undermines capital deepening and slows the process. Spatial effects further reveal that while climate shocks in neighboring regions generate negative spillovers, regional economic expansion contributes positively by accelerating the attainment of steady states in adjacent areas.

From a policy perspective, these findings underscore the need for a regionally coordinated development strategy that integrates climate resilience, sustained investment, and interregional cooperation. Policymakers should prioritize long-term capital accumulation, enhance the quality of human capital to ensure productivity gains, and design climate adaptation policies tailored to local topographies and vulnerabilities. Moreover, strengthening cross-provincial collaboration in mitigating climate risks and leveraging economic spillovers is essential to promote equitable and sustainable regional convergence.

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