Iranian Economic Review, 29(3), 841-867
DOI: 10.22059/IER.2024.352776.1007601

RESEARCH PAPER

Spatial Linkage between Natural Disaster and Poverty in the Archipelago Country (Case Study: Indonesia)

Nur Aini Hidayati[*,a], Deni Kusumawardani[a], Yessi Rahmawati[a], Ana Martina[a], Kemala Sari Agusti[a], Yessy Yuliana Amalia[b], Nurul Fitri Ramdaniyah[c]

a. Department of Economics, Faculty of Economics and Business, Universitas Airlangga, Surabaya, Indonesia.
b. Research Institute of Socio-Economic Development, Surabaya, Indonesia.
c. Green Living Support, Surabaya, Indonesia.
* Corresponding author

Received: 21 December 2022, Revised: 28 November 2023, Accepted: 23 December 2023, Published: 30 September 2025
Publisher: The University of Tehran Press.

Abstract
This study employs spatial econometric modeling to investigate the relationship between natural disasters and poverty in Indonesia. Panel data spanning 2011 to 2019 are sourced from reputable authorities, including the Central Bureau of Statistics and the Natural Disaster Management Agency of the Republic of Indonesia. Empirical findings confirm the presence of spatial autocorrelation in provincial-level poverty in Indonesia, indicating interdependence among neighboring regions in terms of poverty dynamics. This study deviates from existing literature by revealing a surprising result: natural disasters are statistically associated with reduced provincial-level poverty. This counterintuitive outcome underscores the importance of governmental policies, programs, and external financial aid in mitigating the impact of natural disasters. Financial assistance and empowerment initiatives from third-party entities, such as NGOs, religious organizations, and youth groups, play a crucial role in helping disaster-affected communities. These findings offer valuable insights for policymakers. They can use this research to inform disaster response strategies and develop targeted poverty reduction programs at both inter-provincial and inter-regional levels. Ultimately, this study contributes to the understanding of the complex relationship between natural disasters and poverty in Indonesia, with implications for policy formulation and disaster resilience efforts.
Keywords: Indonesia, Natural Disaster, Poverty Reduction, Spatial Econometrics Modelling, Spatial Autocorrelation.
JEL Classification: C33, I3, Q54.

1. Introduction

Indonesia is classified as a disaster-prone country (World Bank, 2019). This situation is inseparable from the geographical condition of Indonesia, which is an archipelagic country and is located at the confluence of four world plates, namely the Asian Continental Plate, the Australian Continental Plate, the Indian Ocean

Plate, and the Pacific Ocean Plate. In the southern and eastern parts of Indonesia, there is also a volcanic arc that extends from the islands of Sumatra, Java-Bali-Nusa Tenggara, north of Sulawesi-Maluku, to Papua. This condition has the potential to cause geological disasters such as volcanic eruptions, earthquakes, and tsunamis. Not only these conditions, but the combination of Indonesia's climatic and topographical conditions also has the potential to cause hydrometeorological disasters such as floods, landslides, forest fires, and droughts (BNPB, 2016).

As a disaster-prone country, the frequency of disasters that occur in Indonesia can potentially threaten socio-economic stability, especially in cases of poverty. It was recorded that during 2021, there were 2,109 natural disasters with the value of losses reaching 1.172 trillion rupiah, which is almost 14.5 percent compared to the total GDP. This condition is exacerbated by the number of victims suffering and evacuating, as well as damage to houses and public facilities (Natural Disaster Management Statistics, 2020). Tasri et al. (2022) stated in their study that catastrophic events in Indonesia can have a direct impact on unemployment and poverty. Natural disasters may cause loss of livelihood, social and economic disruption (Awasthi, 2019). The existence of this natural disaster will also cause damage to the environment and residents' housing, which inhibits residents' activities to earn income (McMahon, 2007). More specifically, a disaster can also destroy people's assets and savings, which has the potential to plunge a person into a 'poverty trap' because productivity decreases significantly, making it difficult for them to rebuild their savings and assets (Carter et al., 2007).

However, growing literatures claim contradictory results on the impact of natural disasters on poverty. Although several studies have shown that natural disasters can affect and increase poverty (Awasthi, 2019; Kawasaki et al., 2020; Winsemius et al., 2018), some studies actually give opposite results. There are several researchers have found that natural disasters are not directly linked with reducing poverty or have no significant effect (Abdullah et al., 2016; Groeschl and Noy, 2020; Warr and Aung, 2019). Leichenko and Silva (2014) found that disasters did not directly affect poverty, but other factors were responsible for worsening poverty, especially in less developed regions. However, it also depends on how policymakers respond to the natural disaster, yearly or seasonal natural disaster, which means natural disasters that happen every season or every year will continuously provide negative externalities on the affected area, which will cause the poor to become poorer (Fang et al., 2017; Miljkovic and Miljkovic, 2014).

Research on the effect of disasters on poverty in Indonesia has been conducted by Putra (2017), which shows that households affected by disasters are more likely to experience poverty. At the household level, Putra (2017) claimed that natural disasters, especially floods and mountain eruptions, are statistically significant influences on poverty compared to other types of natural disasters. However, the research studies done by Putra (2017) could not examine the spillover effect of natural disasters between regions, which actually will give the policy maker a better helicopter view of these issues and can generate more impactful policy recommendations that will help or enable thousands of people to survive from poverty when the disaster occurs. In addition, another research study focusing on Indonesia at the provincial level has been done by Tasri et al. (2022) to examine unemployment and poverty to a natural disaster. This study revealed that poverty and unemployment can increase the loss from natural disasters.

The differences in the results of previous literature reviews provide a signal that different geographical and regional contexts may lead to different empirical results. To address the research gap from the previous study, the present research aims to challenge the spatial approach to analyze the effect of natural disasters on poverty in Indonesia. This research is unique and contributes to the literature through model development and analysis that has never been done before. This study also uses a different method from previous research, namely, by using spatial analysis to reduce the heterogeneity of each province in Indonesia. This model is expected to be the basis for developing a theory about the impact of natural disasters on poverty at the provincial level. At the application level, this model is expected to be an evaluation model to see the effectiveness of disaster management and formulate strategic policies for poor communities affected. In the realm of theoretical investigation, this study seeks to engender a more profound understanding of the intricate nexus between natural disasters and poverty. The ambit of inquiry extends beyond the methodological innovation to encompass broader economic dimensions, notably exploring the intricate relationships with provincial gross domestic product (GDP) and key indicators of human development. The import of our findings transcends the novelty of the employed methodology, encapsulating the substantive integration of pivotal variables that enrich the analytical depth and scholarly significance of this research endeavor. The findings from this study will provide further recommendations on disaster risk reduction strategies, post-disaster recovery efforts, and the design of sustainable development programs

2. Literature Review

Natural disasters have been a recurring phenomenon throughout human history, causing immense destruction and often exacerbating poverty in affected regions. This literature review aims to explore the complex relationship between natural disasters and poverty by examining existing theories, research, and empirical evidence. The grand theory of natural disaster on the scope of economics has been published by Albala-Bertrand (1993). This grand theory measures the impact of natural disasters on the macroeconomic variables, namely capital and growth rate output. The assumption for this theory is (i) a Natural disaster has already taken place within the country; (ii) the country has capital stock; (iii) the disaster reduces stock capital in the long term; (iv) all losses are capital stocks; and (v) capital stocks are homogeneous. Moreover, the grand theory can be explained in the following equations:

$$\Delta K = D \; where \; \Delta K = K_a - K_b \tag{1}$$

where:

K: Capital

D: Total disaster loss

a: before the disaster impact

b: after disaster impact

with the assumption that the global capital-output ratio fluctuates so that it can defer for the loss of capital will be deferred.

$$c = \frac{K}{Y} = \frac{\Delta K}{\Delta Y} \tag{2}$$

where:

c: Capital Output Ratio

ΔY=$Y_a - Y_b$ (The expected output loss)

Y = Output (Income)

By solving equation 2 for ΔY and substituting $\Delta K$for D:

$$\Delta Y = \frac{D}{c} \tag{3}$$

$$y = \frac{d}{c} \tag{4}$$

where:

$\frac{\Delta K}{\Delta Y}$: The growth rate of output

$d = \frac{D}{Y}$: Loss to output ratio

Hallegatte and Przyluski (2010) developed the concept study published by Albala-Bertrand (1993), by adding more comprehensive models, such as including direct and indirect losses from natural disasters. In these cases, Hallegatte and Przyluski (2010) explained that several negative effects from natural disaster do not have market value, hence, it's really hard to measure. From the national development point of view, one of the indirect effects of natural catastrophes is poverty and income inequality.

From the development of the theory of the influence of disasters on poverty, two main theories were obtained: the first is the vulnerability framework, in which poverty makes a person more vulnerable and plunges them into more severe poverty as a result of natural disasters through capital losses. The second scheme is through social capital and resilience. Several studies show that the role of social capital in mediating the impact of natural disasters on poverty.

Natural disasters can affect poverty through the capital channel. This argument is in line with the results of previous studies, which have been studied by researchers for several decades. Some studies found that natural disasters reduced income and increased poverty (Karim and Noy, 2016; Khan et al., 2020; 2021). This statement is also in line with the findings of Bui et al. (2014) for the case of Vietnam, where natural disasters reduce income and increase poverty both in the affected area and the overall population. The resulting impact had a shocking effect on income, and poor households have difficulty adjusting in the post-disaster recovery (Warr and Aung, 2019). In addition, natural disasters can cause households with subsistence livelihoods to be trapped in a cycle of poverty where their assets are lost (Duncan et al., 2017). Another interesting study related to the indirect link between natural disasters on poverty was published by Ngoran et al. (2015). These studies explained that the bad infrastructure and water resources can leave unfortunate people no choice other than stay in poverty when a disaster occurs.

The second scheme is about social capital and resilience; poverty dynamics occur. Leichenko and Silva (2014) analyzed the relationship between climate change disasters and poverty. They found that disasters did not directly affect poverty, but other factors were responsible for worsening poverty, especially in less developed regions. However, it depends on how policymakers respond to the natural disaster. Yearly or seasonal natural disasters will continuously provide negative externalities on the affected area, which will cause the poor to become poorer (Fang et al., 2017; Miljkovic and Miljkovic, 2014). The government should handle the yearly or seasonal natural disasters by creating policy packages that will lower the impact of natural disasters.

The impact of natural disasters on poverty spans critical life sectors. Primarily, disasters can lead to Physical Damage to Infrastructure. Events such as hurricanes, earthquakes, floods, and wildfires can cause extensive harm to infrastructure, including factories, transportation networks, and utilities. Industries relying on physical facilities, like manufacturing, energy, and transportation, may encounter production halts, supply chain disruptions, and increased operational costs due to repair and reconstruction efforts. An additional study by Ngoran et al. (2015) emphasizes the indirect link between natural disasters and poverty. It underscores that poor infrastructure and limited water resources can leave vulnerable populations with no alternative but to remain in poverty when disasters occur.

In the business and industrial sectors, disasters can result in Supply Chain Disruptions. These events often disrupt supply chains by damaging production facilities, transportation routes, and warehouses. Industries reliant on a consistent flow of raw materials and components, such as manufacturing, electronics, automotive, and agriculture, are particularly affected. Supply chain interruptions can lead to shortages, increased costs, and delays in delivering goods and services (Alam and Ali, 2023). Supply chain impacts and reduced demand resulting from natural disasters can also lead to Business Interruption and Loss of Revenue. Industries relying on continuous operations, such as tourism, retail, and hospitality, may experience substantial revenue losses due to business interruptions caused by natural disasters. Temporary closures, reduced consumer demand, and a decline in tourist inflow can result in financial setbacks and long-term economic repercussions (Ngin et al., 2020; Shen et al., 2023; Siodla, 2021).

In addition to the industrial sector, natural disasters can impact the income of the agricultural sector. Agriculture, being particularly vulnerable to disasters like droughts, floods, storms, and wildfires, can experience crop damage, livestock losses, and infrastructure destruction, disrupting food production. This disruption can lead to food shortages, price fluctuations, and economic instability in regions dependent on agriculture (Hua et al., 2023). Moreover, as a logical consequence of disaster mitigation efforts, changes in environmental regulations and policies may occur. Stricter regulations post-disaster can affect industries with environmental footprints, such as mining, energy production, and chemical manufacturing, necessitating costly upgrades or changes to comply with new standards (Boonmee et al., 2021; Joshi and Nishimura, 2016; Siriwardhana and Kulatunga, 2023)

Another study focused on natural disaster on developing countries such as Vietnam where natural disasters reduce income and increase poverty both in the affected area and the overall population (Bui et al., 2014). The impact of natural catastrophic such as natural disaster had a shocking effect on income, and poor households have difficulty adjusting in the post-disaster recovery (Warr and Aung, 2019). In addition, natural disasters can cause households with subsistence livelihoods to be trapped in a cycle of poverty where their assets were lost (Duncan et al., 2017). Another interesting studies related to indirect link between natural disaster on poverty is published by Ngoran et al. (2015). These studies explained the bad infrastructure and water resource can leave unfortunate people no other choice other than stay in poverty when disaster occurs. In the household level analysis, Ahmad and Afzal (2021) studied using the survey data of 398 households of erosion-prone riverbank area of Punjab, Pakistan. They found that natural disasters increased vulnerability and obstacles to socio-economic. It is in line with the study of Arouri et al. (2015) in Vietnam, they found that all the three disaster types considered in their study including storms, floods, and droughts have negative effects on household income and expenditure.

The influence of disasters on poverty can vary in magnitude across different locations. The value of the impact of disasters on economic aspects in the form of capital and income is strongly influenced by the level of risk and social vulnerability. Due to the unequal risk between poor and rich people, each person experiences the different impact of natural disaster. Less developed countries experienced worsen human impact than developed countries due to natural disasters, yet developed countries suffered larger economic losses (Tselios and Tompkins, 2019). The reason behind it is because the disaster mitigation plan, for example less developed countries that do not have an infrastructure, house and building that is resilient from natural disaster will make more people in dangerous situation compared to developed countries who are more prepared with advanced technology and less human loss. However, the contradictory argument stated by Sawada and Takasaki (2017) that is economic losses due to natural disasters experienced by non-poor people were greater than poor people. This is because the proportion of financial assets and physical assets of rich people is greater.

The reality of the differences in risk and vulnerability that affect the economic and financial impacts refers to disaster management theory. Disaster management theory emphasizes; (i) Prevention encompasses activities focused on long-term risk assessment and reduction; (ii) Preparedness involves two main components: monitoring and detection, followed by forecasting and prediction; (iii) Response consists of two aspects: damage assessment and post-disaster coordination; (iv) Lastly, recovery involves the reconstruction and restoration of infrastructure (Djoumessi and Mbongo, 2022). Based on this theory, every location where a disaster occurs can either exacerbate or have no effect on poverty.

The magnitude of the impact of disasters on poverty can be influenced by two things, namely vulnerability and coping aspects. First, the risk of natural disasters is not distributed equally among people thus leads unequal resilience and vulnerability. Poorer people have a greater risk of natural disasters or other negative externality because poorer citizens generally are not ready. Second post-disaster, usually the richer have a better coping mechanism by using their saving and asset to manage their sufficient spending for everyday life, while the poorer only rely on the government and third parties' support. In another hand, in a macroeconomic level natural disaster is not directly multiplying the number of poor people but channeling by economic growth and financial development in each country (Lee and Tang, 2019). However, this has become the reason why the growing literature claims a contradictory results on how the impact of natural disasters on poverty.

In this study, other factors that influence poverty are captured through two explanatory variables, namely Gross Domestic Product (GDP) and Human Development Index (HDI). The GDP variable in this study refers to the theory of economic growth that is generally economic growth will reduce the level of poverty in macroeconomic level. To support the previous statements, an empirical study has proven that an increase in GDP by 10 percent can reduce poverty by 4 to 5 percent (Balasubramanian et al., 2023; Li et al., 2015; Siburian, 2022). The HDI variable captures the quality of human capital in each province. The quality of human capital plays an important rule in making household survive from internal and external shock. According to production theory, increasing the aspect of human capital can increase income (Todaro and Smith, 2012). The increase in HDI is also able to reduce poverty (Ottoni et al., 2018). The community organization, Non-Governmental Organization and other third parties will also make a big move to help the affected area. All of those could make a biased result of the impact of natural disasters on poverty. In addition, the inconsistent result can also be caused by the sample size, the absolute size of the income shock caused by the disaster, and the size of poverty (Warr and Aung, 2019).

Previous research, such as the study conducted by Rush in 2018, has shed light on the interconnectedness of disasters and poverty in Indonesia. It highlighted that poverty amplifies an individual's vulnerability to the adverse effects of disasters. However, it is crucial to note that this particular investigation primarily focused on the impact of disasters on the education sector, leaving a notable gap in our understanding of the broader poverty-disaster nexus. Another valuable contribution to the literature was made by Putra (2017), who utilized microdata from the Indonesian Family Life Survey (IFLS) and employed the Linear Probability Model (LPM) method. This study, while significant, offered insights into the varying effects of disasters on poverty. Specifically, it demonstrated that events such as volcanic eruptions and floods can exert a substantial influence on poverty levels within Indonesia. However, it is worth mentioning that Putra's research did not delve into the intricate relationship between regions affected by disasters, thus leaving an important aspect unexplored. The present research seeks to bridge these gaps by adopting a novel approach—spatial analysis. Spatial analysis offers a more comprehensive perspective, as it allows for a holistic assessment of the overall economic and social conditions in each province across Indonesia. Importantly, it facilitates the examination of how a disaster's impact in one region can reverberate through spatial interdependencies, affecting neighboring provinces. By incorporating this spatial dimension, this research endeavors to provide a deeper and more nuanced understanding of how disasters influence poverty dynamics in Indonesia, thereby advancing the existing body of knowledge on this critical issue.

3. Data and Methodologies

3.1 Study Area and Focus

The geographical area of the present research studies consists of more than 17.000 islands divided into 34 provinces from Sabang to Merauke in 2022. Indonesia is an archipelago country that has an abundance of natural resources and is also prone to natural disasters every year. The main aim of this research is to further examine the linkages between natural disasters and poverty in the archipelago country, namely Indonesia. The data used in this paper mainly include spatial data and panel data of social economics, which will be explained further in Table 1. The spatial data are downloaded from Here. The panel data are collected from 2011 to 2019, from various sources, namely the Central Bureau of Statistics and the Natural Disaster Management Agency of the Republic of Indonesia.

Many researchers have different types of measurement for natural disasters, some of them using indices of natural disasters, such as Li et al. (2015) and Nepal et al. (2021), or the impacted people, death, or fatality, such as Akther et al. (2022), Hallegatte et al. (2020), Kim and Marcouiller (2015), and Padli et al. (2018), and economic losses, such as Ngoran et al. (2018), from natural disasters. Considering the majority of the literature review is based on the literature review paper published by Hallegatte et al. (2020), the present research uses the impacted or affected people to measure the impact of all natural disasters. The impacted people face death or fatality because of natural disasters and natural disaster survival. Unfortunately, the present research sees natural disasters as general, not by a specific reason. We noted that each natural disaster had a different impact on society; nevertheless, the authors could not accommodate all the different impacts in the economic modeling. The socio-economic aspect of the society will be captured by GDP and HDI (Fang et al., 2017; Li et al., 2015).

Table 1. The Variable Description

Variables	Acronym	Definition	Source
Spatial Data	-	Shape File of Indonesia	https://tanahair.indonesia.go.id/portal-web
Poverty	LnPOV	The total population living under poverty in each province.	Central Bureau of Statistics, Republic of Indonesia
Natural Disaster	LnDIS	The affected people are when the catastrophe occurs.	Natural Disaster Management Agency of Indonesia
GDP	LnGDP	Regional Gross Domestic Product	Central Bureau of Statistics, Republic of Indonesia
HDI	HDI	Human Development Index	Central Bureau of Statistics, Republic of Indonesia

The spatial econometric model used to answer the present research question is generated from 34 provinces. The authors reviewed many variables from the previous studies before deciding to use the main and control variable for the present research. The general equation for the present research will be shown by Equation 5 and Statistic Descriptive of the data used for the present research are explained in Table 2.

$$LnPov_{it} = \beta_0 + \beta_1 LnDisaster_{it} + \beta_2 LnGDP_{it} + \beta_3 LnHDI_{it} + v_{it} \quad (5)$$

Table 2. Statistic Descriptive

No	Variables	Obs	Mean	Std Dev	Min	Max
1	LnPoverty	288	6.118044	1.05906	4.199005	8.586012
2	LnDis	288	4.641852	3.35548	0	14.71227
3	LnGDP	288	12.09413	1.177896	9.745555	14.85961
4	LnHDI	288	4.22669	0.065682	4.007515	4.391482

Source: Research finding.

The utilization of spatial econometrics in this research is of paramount importance as it aims to examine the relationship between natural disasters and poverty in Indonesia. By employing spatial econometric modeling techniques, the study explores panel data collected from 2011 to 2019, sourced from the Central Bureau of Statistic and the Natural Disaster Management Agency of the Republic of Indonesia. The findings of the research reveal the presence of spatial autocorrelation in poverty at the provincial level, underscoring the interdependence of poverty outcomes across neighboring regions in Indonesia. This identification of spatial autocorrelation provides valuable insights into the geographical distribution of poverty, shedding light on the factors influencing poverty disparities throughout the country. The insights have significant implications for policymakers, aiding in the formulation of targeted and evidence-based poverty reduction programs. By leveraging spatial econometric modeling techniques, policymakers can enhance their understanding of the geographical distribution of poverty, effectively allocate resources, and develop strategies to assist survivors of natural disasters in their journey towards recovery and resilience.

3.2 Spatial Econometrics

The central goals of the present research are to empirically examine the regional interconnectedness of poverty after a natural disaster strikes. Since the end of the 1950s, the study regarding spatial linkages has been based on a theoretical and practical approach already developed by many researchers who focus on regional economic development. Elhorst (2014) explained that regional economic development can't distinguish between the concept of spaces and time in a different region. The spatial data is applied because the author hypothesizes that there is spatial dependence or interdependence among provinces that is observed. The spatial econometric methodology can perfectly observe, examine, and show by map the result of regional interdependence and autocorrelation (Anselin, 2003; Anselin et al., 2011). Spatial autocorrelation can be classified into two types: the first is clustering, which shows the coefficients of spatial autocorrelation are positive, and the second is dispersing, which shows the coefficients are negative. The spatial weighted matrix is generally a matrix that consists of 0 and 1 values (Anselin et al., 2011). This matrix demonstrates spatial interdependence or contiguity that has the symbol of W and is built based on the information of distance, neighbors' area, and neighborhood area.

The first step of spatial econometrics will be to generate Moran's test (Moran, 1948), which involves conducting the preliminary analysis to see if there is spatial autocorrelation among the regions or not. The Moran I Test generates the ratio amongst cross-products of deviations from the mean of the variable of interest and their corresponding spatial intervals, along with the square of assessed deviations:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \, (y_i - y)(y_j - y)}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \; \sum_{i=1}^{n} (y_i - y)^2} \tag{6}$$

The coefficient of Moran-I index will be in the range -1 < I < 1. If the I > 0 so we can conclude the Index reflects there is positive clustering, while if the I < 0 is dispersing (Anselin et al., 2011; Elhorst, 2014).

The general assumption of spatial econometric analysis is that there is a spatial interdependence between observed regions, for example, local variables with neighboring WY, interaction between independent variables with local dependent variables WX, and error term interactions with local dependent variables Wu (Elhorst, 2014). The economics modeling of spatial econometrics is based on General Nesting Spatial Models (GNS) with the equation follows:

$$Y = \delta WY + \alpha_n + X\beta + WX\theta + u \quad (7)$$

where $u = \lambda Wu + \varepsilon$.

Where: δ is the coefficient of Spatial Autoregressive, λ is the coefficient of spatial autocorrelation, and θ, like β, represents the vector of Kx2 from the fixed parameter but unknown to be estimated. W is a non-negative matrix n x X that represents the spatial configuration. From the GNS model, Belotti et al. (2017) classified the model as follows:

SDM (Spatial Durbin Model)

$$y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij}\, y_{jt} + \sum_{k=1}^{K} x_{itk}\, \beta_k + \sum_{k=1}^{K} \sum_{j=1}^{n} w_{ij}\, x_{jtk} \theta_k + \mu_i + v_{it} \quad (8)$$

SAR (Spatial Auto-regressive Model- Spatial Lag)

$$y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij}\, y_{jt} + \sum_{k=1}^{K} x_{itk}\, \beta_k + \mu_i + v_{it} \quad (9)$$

SEM (Spatial Error Model)

$$\begin{aligned} y_{it} &= \alpha + \sum_{k=1}^{K} x_{itk}\, \beta_k + \mu_i + v_{it} \\ v_{it} &= \lambda \sum_{j=1}^{n} w_{ij}\, v_{it} + \epsilon_{it} \end{aligned} \quad (10)$$

SACFE (Spatial Autoregressive Combined Model)

$$\begin{aligned} y_{it} &= \alpha + \rho \sum_{j=1}^{n} w_{ij}\, y_{jt} + \sum_{k=1}^{K} x_{itk}\, \beta_k + \mu_i + v_{it} \\ v_{it} &= \lambda \sum_{j=1}^{n} w_{ij}\, v_{it} + \epsilon_{it} \end{aligned} \quad (11)$$

GSPRE (Generalized Spatial Panel Random Effect Model)

$$\begin{aligned} y_{it} &= \alpha + \sum_{k=1}^{K} x_{itk}\, \beta_k + \mu_i + v_{it} \\ v_{it} &= \lambda \sum_{j=1}^{n} w_{ij}\, v_{it} + \varepsilon_{it} \\ \mu_i &= \phi \sum_{j=1}^{n} w_{ij}\, \mu_i + \eta_i \end{aligned} \quad (12)$$

The maximum likelihood (ML) estimation produces consistent estimators for all the spatial econometric models, if the estimated model follows the true data generating process (Lee and Wong, 2001) while the OLS (Ordinary Least Squares) estimators are inconsistent. This study estimates the models in the above five spatial specifications with the ML approaches using the STATA codes provided by Belotti et al. (2017).

4. Result and Discussion

4.1 Empirical Finding

The existing study wants to empirically explain the linkage between Natural disasters and poverty in developing countries, namely Indonesia. First, the authors conducted Moran's I test to examine the spatial autocorrelation between provinces in each variable. Table 3 confirms that there is spatial autocorrelation and it is statistically significant clustering. Meanwhile, the dispersing patterns are found in GDP and Natural disasters, but it’s not statistically significant. Since it confirms there is more than one variable that has an inter-regional linkage, the authors need to proceed to the next step of spatial econometrics analysis.

Table 3. Moran-I Test

Contiguity Matrix	Moran-I test Variable	Coeff	P-Value
Distance	Poverty	0.257**	0.0520
	Natural Disaster	-0.072	0.353
	GDP	-0.167	0.134
	HDI	0.237**	0.0380
Rook Contiguity	Poverty	0.230**	0.060
	Natural Disaster	-0.073	0.343
	GDP	-0.179	0.103
	HDI	0.267**	0.067
Queen Contiguity	Poverty	0.592**	0.0050
	Natural Disaster	-0.128**	0.077
	GDP	-0.179	0.103
	HDI	0.267**	0.067

Source: Researcg finding.

Considering the impact of natural disaster on poverty, since the poverty and HDI are clustering and have significant positive spatial spillover effect supported previous research in the tourism sector (Romão and Saito, 2017; Sun et al., 2018; Yang and Wong, 2012), Solid Waste Management (Cerciello et al., 2019; Gui et al., 2019; Ouchen and Montargot, 2021; Wang et al., 2021). However, the similar result is also found in the natural disaster sector namely flood (Kim et al., 2021; Nepal et al., 2021; Pathak and Olmo, 2021; Rosalia et al., 2021; Zhou et al., 2021).

According to the Moran's p value which is shown by Table 3, revealed that poverty has value below 0.05 in queen contiguity (0.592), rook contiguity (0.230) and distance (0.257), this study can successfully claim that there is a positive spatial autocorrelation or the location of an area has an influence on the level of poverty. Poverty cases between provinces in Indonesia are interconnected when viewed from the location of the eight cardinal directions, fourth cardinal direction and based on the distance. A province can have a high poverty rate if it is adjacent to a province with a high poverty rate and vice versa. Meanwhile, the variables of natural disaster and GDP have a p-value of more than 0.05, which means that they do not have spatial autocorrelation between provinces. Considering the topography and geographical location of Indonesia, which is surrounded by sea, using queen and rook contiguity might be leading the bias result. So, for the present research the authors decided to use the distance for further estimations.

Next estimation, the author will explain the result of the empirical findings of spatial econometrics that is shown by Table 4. The authors estimate the relationship between natural disaster and poverty in 6 modeling economics which we adopted from Anselin et al. (2011) and Elhorst (2014), namely SDM, SAR, SEM, GSPRE and SACFE. First, the author will focus on the spatial autocorrelation in the present research. The value of rho (ρ) in SDM (FEM and REM) and SAR (FEM and REM) modeling shows significant results in the 1, 5, and 10 percent, respectively. These results from two models supported the previous Moran I result which as expected. The value of lambda in SEM modeling shows significant results in the 1 percent level of significance, respectively. So, it can be said that at the poverty level there is a spatial error dependency. These results were validated by the statistically significant GSPRE and SACFE models. This indicates a significant spatial heterogeneity which means there is autocorrelation between regions in the case of poverty or in another word the increase of poverty in one region can be determined by the increase of poverty in neighboring regions. The results of the SDM, SAR, and SEM modeling have similar results in terms of coefficients and significance. However, the best model is shown by the SDM model with an AIC value of 0.228. Therefore, for the next estimation, the authors only focus on SDM results with FE and RE models.

Along with spatial autocorrelation estimation, now we focus on the relationship between the independent variable and dependent variables. The results also shows that the sign of the coefficient of each variable has the same in all spatial models in the levels of 1, 5, and 10 percent of significance, respectively. First, we focus on the relationship between natural disaster on poverty which reveals there is strong and negative relationship between these variables in the levels of 1, 5, and 10 percent of significance. Thus, it can be verified that the presence of natural disasters can negatively affect poverty which is not supported the previous studies. However, the other independent variables such as GDP and HDI are also negatively influence the poverty in the area.

The local spillover can be seen from the regression of the W_x Matrix shown in Table 2 that is one of the benefits of using the SDM model. The present research reveals the relationship between HDI from neighboring provinces can statistically increase the poverty in one region as can be seen from the P-value for HDI for both FEM and REM are statistically significant at 1 percent level of significance. However, the present research reports the increase of GDP in neighboring provinces can reduce the level of poverty by 0.0003.

Table 4. Empirical Findings of Spatial Econometrics

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
	SDM		SAR		SEM		GSPRE	SACFE
	FEM	REM	FEM	REM	FEM	REM	REM	FEM
LnDIS	-7.7589***	-7.665212**	-9.843516***	-9.364869**	-9.968833***	-9.575451**	-9.382558**	-9.12055***
	(0.031)	0.044	(0.007)	(0.016)	(0.008)	(0.016)	(0.018)	(0.008)
LnGDP	-0.0002605***	-0.0002339***	-0.0002754***	-0.0002442 ***	-0.0002666***	-0.0002376***	-0.0002342***	-0.0002829***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDI	-143.2638***	-130.3343***	-10.18875*	-11.51179**	-16.29082**	-18.08154**	-19.49525**	-2.170217
	(0.000)	(0.000)	(0.111)	(0.087)	(0.027)	(0.021)	(0.014)	(0.716)
cons		321.7825		1626.738***		2227.368***	2332.435***	
		(0.582)		(0.001)		(0.000)	(0.000)	
Wx								
LnDIS	-3.062473	-2.653587						
	(0.582)	(0.652)						
LnGDP	-0.0003432***	-0.0003112***						
	(0.000)	(0.001)						
HDI	154.0724***	139.4938***						
	(0.000)	(0.000)						
rho	0.1051131*	0.153**	0.153313**	0.1799377***			0.364***	0.3639051***
	(0.103)	(0.0625)	(0.014)	(0.004)			(0.000)	(0.001)
sigma2_e			20,120***		20322.82***	22861.53***	151.1983***	20985.13***
			(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
sigma2_mu							1147.307***	
							(0.000)	
lambda					0.1313863**	0.142379**	0.1455849**	-0.2683031**
					(0.055)	(0.048)	(0.044)	(0.040)
phi						4.273546***	0.4431611**	
						(0.000)	(0.016)	
Observations	288	288	288	288	288	288	288	288
AIC	0.228	0.228	0.228	0.303	0.303	0.303	0.303	0.303
Number of id	32	32	32	32	32	32	32	32

Source: Researcg finding.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.2 Discussion

The present findings establish a strong negative relationship between the impact of natural disaster and poverty in Indonesia. Remarkably, the author can claim that the existing natural disaster can reduce the poverty in Indonesia which is really interesting to discuss. Figure 1 establishes the impact of natural disaster on Poverty in each region, providing a comprehensive visual representation supporting the central argument of the present research. Notably, all provinces in Papua, central and western Java exhibit the highest impact on poverty when disaster happens, while Kalimantan and Sulawesi Island demonstrate the lowest impact. Flood, the most frequent natural disaster in Papua, Central Java, and Western Java may be a contributing factor, trapping people in the cycle of poverty (*Natural Disaster Management Statistics*, 2020). Despite regional variations, the overall result of this study presents an intriguing outcome – natural disasters appear to have a positive impact on reducing poverty. This counterintuitive finding challenges conventional wisdom and suggests the necessity for further exploration and nuanced understanding of the complex relationship between natural disaster and poverty in Indonesia.

This finding is supported by Abdullah et al. (2016), particularly in the context of typhoons in Bangladesh. Their results revealed that after a natural disaster, poor people earn higher incomes than before after natural disaster occurred. The reason could be that the poorer people experienced an increase in income compared to the pre-disaster level. It appears that these individuals seized new opportunities generated by the aftermath of the disaster, leading to an income boost of more than 15 percent over the average income before. Similar cases in Myanmar have provided evidence of post-disaster poverty reduction (Warr and Aung, 2019) and creation of new sources (Groeschl and Noy, 2020). Warr and Aung (2019) observed that, in the short term, poorer individual tends to manage their consumption at the minimal level when a disaster strikes, while in the long term, they actively seek opportunities and jobs to recover. Importantly, these positive outcomes do not result directly from the impact of the disaster itself, but rather from effective policies and programs aimed at addressing the consequences of the disaster. Social protection policies and guarantees for those affected by the disaster play a crucial role in poverty reduction resulting from natural disasters.

While this study establishes that disasters can reduce poverty, it is essential to acknowledge the contextual nature of this finding. Hallegatte et al. (2020) and Xiang et al. (2021) highlight the diverse geographical, topographical, and climate condition across the islands in Indonesia, leading to varied vulnerabilities and risk for each population. This diversity prevents the generalization of disaster poverty pattern across the entire country. A similar complexity is observed in Sichuan Province, where not all regions exhibit a clear clustering of the natural disaster-poverty relationship. Moreover, the contextual variations extend to regulatory differences in each country, further influencing the interplay between natural disaster and poverty. It is crucial to consider these nuanced factors when interpreting the study's findings and when formulating policies and strategies for disaster resilience and poverty reduction in specific regions.

Furthermore, the impact of disasters on poverty is intricately linked to the level of resilience within households in a given area. If the effect of disasters on income is substantial, the likelihood of a significant impact on poverty increases. Conversely, the impact is marginal, and the probability of a household falling into poverty diminishes. Thus, the occurrence of a disaster does not necessarily guarantee an increase in the poverty status of a household (Putra, 2013). Menendez (2014) supports this perspective between natural disasters on poverty in Indonesia, highlighting the importance of considering varying time frames in understanding the economic consequences of such events.

As we utilized provincial-level data, the direct consequences of natural disasters on poverty may vary across regions. Moreover, in the long term, areas adjacent to disaster-stricken zones may indirectly benefit from the heightened demand during rehabilitation and reconstruction in the core disaster area (Yu Xiao and Nilawar, 2013). Disasters can also reshape the economic structure of a region, leading to a focus on sectors that demonstrate greater resilience to such events. Production centers may shift to areas that are less vulnerable to disasters, reducing development inequality and creating new job opportunities in proximity to the affected areas. Consequently, at a broader level, natural disasters can indirectly contribute to poverty reduction in the long run. This aligns with the experiences of West Sumatra and Yogyakarta provinces in Indonesia, which demonstrated high positive growth in the years following disasters, consequently impacting poverty reduction (Nazamuddin and Nugroho, 2019). A recent study by Ilham et al. (2023) similarly found that natural disasters, by influencing regional economic growth, indirectly contribute to poverty reduction in Indonesia.

Disasters, often viewed as 'blessings in disguise', present opportunities for rebuilding and improving outcomes, including the potential to mitigate future disasters (Bănică et al., 2020). They serve as a valuable learning experience on how to cope with extreme shock, offering insights for enhancing resilience. Additionally, disaster injects economic stimulus into the affected development through insurance mechanism and support from both private and public sector (Rose, 2014). In the aspect of government policies addressing the natural disaster, Indonesia has implemented various packages of policies at the national, regional, and local levels. These policies encompass substantial financial assistance or aid (World Bank, 2021), as well as physical and mental health support from the national and regional level (Marfuah et al., 2021). In terms of budgeting for natural disasters, the Indonesian Government has established an instrument designed to allocate funds for sustainable pre-disaster, emergency response, and post-disaster financing. Social protection mechanisms are recognized as effective tools for enhancing welfare. Post-disaster intervention priorities include efforts to meet people's basic needs, encompassing both food and non-food essentials such as housing, education, and health. This holistic approach underscores the government's commitment to addressing the multifaceted challenges posed by natural disasters and promoting long-term resilience and well-being.

Remarkably, third-party entities such as international, national, and local Non-Governmental Organizations (NGOs), community groups, cooperation initiatives, youth organizations, and religious organizations play significant roles in aiding affected areas and people (Smiley et al., 2018). Indonesia, with its strong societal values emphasizing cooperation ('*Gotong royong*' in Bahasa), witnesses a collective effort to help affected individuals maintain their consumption levels during the initial three months following a shock. The willingness of people to extend assistance and donations, even from regions outside the affected area, coupled with government-provided social protections, reflects the robust sense of community support. Moreover, the provision of social welfare emerges as a critical factor in assisting the most vulnerable populations through disasters (Tselios and Tompkins, 2019). This commitment to social welfare may explain why the impact of shocks after a disaster is often experienced only in the short term in Indonesia, and in certain instances, leads to a reduction in poverty levels.

As anticipated, the coefficient for regional GDP exhibits a significant negative effect. The reduction in the number of poor people appears to be closely tied to economic growth that benefits the impoverished. In line with findings from the World Bank (2006), the post-crisis period saw a substantial decrease in poverty, largely attributed to enhanced economic stability. This outcome suggests that an upswing in regional GDP is associated with the region's capacity to alleviate poverty and its potential to implement pro-poor policies (Li et al., 2015; Siburian, 2022). The extent of disaster losses is intricately linked to the social and economic conditions of the community. Communities with better socio-economic conditions tend to experience lower levels of economic losses (Tasri, 2021). In this context, GDP serves as an indicator of the level of welfare or the capacity for recovery. This finding aligns with a study conducted by Erman et al. (2020), which asserted that individuals in low-income countries, as indicated by purchasing power parity, generally have less protection compared to those in wealthier nations. Regions with higher incomes are more inclined to implement climate risk management strategies and leverage the latest technologies, resulting in reduced risk impacts and losses from disasters (Tasri et al., 2022). It emphasizes the interconnection between poverty alleviation and disaster risk management.

This estimation reveals a negative coefficient for the Human Development Index (HDI), indicating that an increase in HDI correlates with a poverty reduction. Highly developed countries are expected to mitigate the impact of natural disasters, evidenced by a reduction in the total number of casualties, affected individuals, and overall damage. The components of human capital, including education and health, play a significant role in boosting both total factor productivity and creating opportunities for individuals in a country. The Human Development Index (HDI) serves as an indicator of household preparedness to overcome shocks caused by natural disasters. Human development consistently emerges as a key determinant of vulnerability to natural disasters. Improved education, health, and income indicators are associated with a reduced risk of natural disasters (Lutz, 2015). Higher human capital contributes to economic benefits such as enhanced productivity and reduced unemployment (Padli et al., 2018; Teixeira, 2014). Regions with a higher Human Development Index (HDI), as emphasized by Padli et al. (2018), exhibit faster recovery capabilities compared to those with a lower HDI. A heightened HDI acts as a barrier, reducing the fatality rate of disasters and representing an educational level that aids in mitigating natural disasters. Individuals with higher education levels among the affected population tend to be more open to opportunities, promoting increased income and mitigating poverty (Olopade et al., 2019). Public investments in education and health, contributing to higher human capital, have been shown to alleviate poverty in OPEC countries (Olopade et al., 2019). Cheng et al. (2021) support this argument in their latest publication, indicating that human capital, with education playing a prominent role, has a positive effect on poverty alleviation. These findings align with the assertions of Aldino (2018) and Nigrum (2017), who posit that higher HDI levels in an area enhance the quality of human resources, accelerating recovery and reducing poverty in affected areas.

The analysis results indicate that the impact of GDP is smaller compared to the role of HDI in reducing poverty. These findings underscore that addressing poverty solely through increased economic growth, in the anticipation of a trickle-down effect, may not be sufficient. Enhancing the quality of human resources proves to have a more substantial influence on reducing the poverty rate.

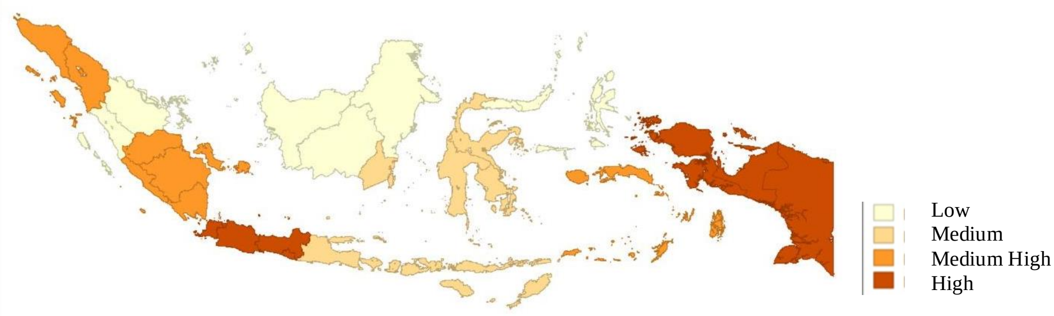

Figure 1. The Impact of Natural Disaster on Poverty in Indonesia
Source: Researcg finding.

With reference to the Sendai Framework, the Paris Agreement, and the agenda for Sustainable Development Goals (SDGs), resilience and disaster mitigation play a crucial role in achieving sustainable development. Aligning with the Global Platform for Disaster Risk Reduction (GPDRR) implementation, Indonesia must not only prioritize disaster-induced poverty but also cultivate an adaptive and responsive institutional culture, along with ensuring adequate funding. Environmental conservation efforts and technological innovation must be synergized for comprehensive progress.

5. Conclusion and Policy Recommendation

The primary goal of this research is to establish the relationship between natural disasters and poverty using Spatial Econometric Modeling. The findings reveal intriguing insights into the impact of catastrophic disasters on poverty. Three key explanations can be derived from the results. Firstly, both the Moran I test and Spatial Econometrics consistently demonstrate spatial autocorrelation in poverty, indicating that the level of poverty in one area can influence neighboring areas. Secondly, the research shows a significant reduction in poverty due to the impact of natural disasters. The distinct geographical, topographical, and climatic characteristics of each province play a crucial role in this outcome. Notably, international, national, and local financial assistance effectively manages the consumption of affected individuals. Additionally, the strong moral value of mutual cooperation among Indonesians contributes significantly to aiding affected people and areas. Thirdly, higher GDP and HDI suggest a more prepared society, enabling faster recovery from negative external shocks. The relationship between GDP and HDI extends beyond education, encompassing familiarity with the latest technological advances. Based on the main finding of the present research, we can generate input for policymakers:

- Due to the spatial autocorrelation of poverty, which allows policymakers to treat poverty as an interregional policy. So, the policymakers need to coordinate between the regional and national levels to generate a poverty alleviation policy. However, the most important part to utilize the spatial autocorrelation based on the present research findings, are joint policy for poverty reduction.
- The strong and negative relationship between natural disasters and poverty is very interesting to discuss. However, the government can maximize the utility of third parties to help affected people and the area. Meanwhile, the assistance or aid from the central and regional government can be increased in order to help people maintain the same level of consumption when there is shock.
- The existing local spillover between HDI and GDP can be utilized by regional government. The joint policies between neighboring areas on one island can be one of the ways to reduce poverty. In addition, since the Government of Indonesia carries out massive inter-region infrastructure development to boost economic growth, it should also be developed to reduce poverty, especially with an emphasis on geographically disaster-prone areas.

- In addition, a structured and holistic disaster management framework involving stakeholders, both central and regional, is very necessary so that the government does not ignore disasters.

To contribute more to the Indonesian Government and society, future studies should incorporate government aid or assistance into econometric modeling. The authors believe that government aid can play a significant role in helping affected individuals. However, poverty is a multidimensional issue, and the authors cannot overlook the social aspects, such as mutual cooperation, religion-based organizations, and other third parties, which provide significant assistance during natural disasters.

Abbreviations:
AIC: Akaike information criterion
Coef: Coefficient
FEM: Fixed Effect Model
GDP: Gross Domestic Product
GPDRR: Global Platform for Disaster Risk Reduction
GSPRE: Generalized Spatial Panel Random Effect Model
HDI: Human Development Index
ML: Maximum Likelihood
NGOs: Non-Governmental Organizations
OLS: Ordinary Least Squares
OPEC: Organization of the Petroleum Exporting Countries
P value: Probability Value
R2: R-Squared (Squared Pearson's Correlation coefficient)
REM: Random Effect Model
S.D: Standard Deviation
SACFE: Spatial Autoregressive Combined Model
SAR: Spatial Auto-regressive Model- Spatial Lag
SDGs: Sustainable Development Goals
SDM: Spatial Durbin Model
SEM: Spatial Error Model
STATA: Statistics and Data Software

Statements and Declarations

Acknowledgement: This research has been supported by Airlangga University.
Role of the Funder/Sponsor: The funder had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy, have been completely observed by the authors.

Availability of data and materials: Data sharing does not apply to this article, as datasets were generated or analysed during the current review.

Ethics approval: This study did not involve participation of human subjects; therefore, ethical approval was not required.

Informed consent: Not required

References

Abdullah, A. N. M., Zander, K. K., Myers, B., Stacey, N., & Garnett, S. T. (2016). A short-term decrease in household income inequality in the Sundarbans, Bangladesh, following Cyclone Aila. *Natural Hazards*, *83*(2), 1103–1123. Retrieved from https://doi.org/10.1007/s11069-016-2358-1

Ahmad, D., & Afzal, M. (2021). Flood hazards, human displacement and food insecurity in rural riverine areas of Punjab, Pakistan: policy implications. *Environmental Science and Pollution Research*, *28*(8), 10125–10139. Retrieved from https://doi.org/10.1007/s11356-020-11430-7

Akther, S., Rahman, M. M., & Rezwana, N. (2022). The emergence of lightning as a natural disaster in Bangladesh and its impact on household dynamics. Retrieved from https://assets-eu.researchsquare.com/files/rs-1529632/v1/2e742aa3-4fb7-4d5e-b723-67299cdcaba2.pdf

Albala-Bertrand, J. M. (1993). Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development*, *21*(9), 1417–1434. Retrieved from https://doi.org/10.1016/0305-750X(93)90122-P

Aldino, M. (2018). *Poverty Analysis in Central Java*. Yogyakarta: Universitas Islam Indonesia. [In Indonesian]

Anselin, L. (2003). Spatial Econometrics. In B. H. Baltagi (Ed.), *A Companion to Theoretical Econometrics* (310–330). Oxford: Blackwell Publishing Ltd.

Anselin, L., Florax, R. J. G. M., & Rey, S. J. (2011). *Advances in Spatial Econometrics: Methodology, Tools and Applications* (Eds.). Berlin: Springer.

Arouri, M., Nguyen, C., & Youssef, A. Ben. (2015). Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam. *World Development*, *70*, 59–77. Retrieved from https://doi.org/10.1016/j.worlddev.2014.12.017

Awasthi, P. R. (2019). A Relationship between Natural Disaster and Poverty. *Journal of APF Command and Staff College*, *2*(1), 67–69. Retrieved from https://doi.org/10.3126/japfcsc.v2i1.26733

Bănică, A., Kourtit, K. & Nijkamp, P. (2020). Natural disasters as a development opportunity: a spatial economic resilience interpretation. *Review of Regional Research, 40*, 223–249. Retrieved from https://doi.org/10.1007/s10037-020-00141-8

Belotti, F., Hughes, G., & Mortari, A. P. (2017). Spatial panel-data models using Stata. *The Stata Journal, 17*(1), 139-180. Retrieved from https://journals.sagepub.com/doi/pdf/10.1177/1536867X1701700109

BNPB. (2016). Indonesia's Disaster Risk. Publication of the Directorate of Disaster Risk Reduction. Retrieved from https://inarisk.bnpb.go.id/pdf/Buku%20RBI_Final_low.pdf

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics*, *46*(15), 1751–1766. Retrieved from https://doi.org/10.1080/00036846.2014.884706

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty Traps and Natural Disasters in Ethiopia and Honduras. *World Development*, *35*(5), 835–856. Retrieved from https://doi.org/10.1016/j.worlddev.2006.09.010

Cerciello, M., Agovino, M., & Garofalo, A. (2019). Estimating urban food waste at the local level: Are good practices in food consumption persistent? *Economia Politica*, *36*(3), 863–886. Retrieved from https://doi.org/10.1007/s40888-017-0089-8

Cheng, X., Chen, J., Jiang, S., Dai, Y., Shuai, C., Li, W., Liu, Y., Wang, C., Zhou, M., Zou, L., Zhang, P., & Kang, X. (2021). The impact of rural land consolidation on household poverty alleviation: The moderating effects of human capital endowment. *Land Use Policy*, *109*, 105692. Retrieved from https://doi.org/10.1016/j.landusepol.2021.105692

Djoumessi, Y. F., & Mbongo, L. D. B. E. (2022). An analysis of information communication technologies for natural disaster management in Africa. *International Journal of Disaster Risk Reduction, 68*, 102722. Retrieved from https://www.sciencedirect.com/science/article/pii/S221242092100683X

Dube, E., & Oliver Mtapuri, J. M. (2018). Flooding and Poverty: Two Interrelated Social Problems Impacting Rural Development in Tsholotsho District of Matabeleland North Province in Zimbabwe. *Jàmbá: Journal of Disaster Risk Studies*, *10*(1). Retrieved from https://doi.org/10.4102/jamba.v10i1.455

Duncan, J. M., Tompkins, E. L., Dash, J., & Tripathy, B. (2017). Resilience to hazards: rice farmers in the Mahanadi Delta, India. *Ecology and Society*, *22*(4), art3. Retrieved from https://doi.org/10.5751/ES-09559-220403

Elhorst, J. P. (2014). *Spatial Econometrics*. Berlin: Springer.

Erman, A., Motte, E., Goyal, R., Asare, A., Takamatsu, S., Chen, X., Malgioglio, S., Skinner, A., Yoshida, N., & Hallegatte, S. (2020). The Road to Recovery The Role of Poverty in the Exposure, Vulnerability, and Resilience to Floods in Accra. *Economics of Disasters and Climate Change*, *4*(1), 171–193. Retrieved from https://doi.org/10.1007/s41885-019-00056-w

Fang, L., Wu, J., & Miljkovic, T. (2017). Modeling Impact of Natural Hazard-Induced Disasters on Income Distribution in the United States. *International Journal of Disaster Risk Science*, *8*(4), 435–444. Retrieved from https://doi.org/10.1007/s13753-017-0148-3

Fayazi, M., & Bornstein, L. (2021). The links between vulnerability, poverty, and natural hazards: A focus on the impacts of globalization trends. In *Enhancing Disaster Preparedness* (259–272). New York: Elsevier.

Groeschl, J., & Noy, I. (2020). Poverty, Inequality, and Disasters – An Introduction to the Special Issue. *Economics of Disasters and Climate Change*, *4*(1), 1–3. Retrieved from https://doi.org/10.1007/s41885-020-00063-2

Gui, S., Zhao, L., & Zhang, Z. (2019). Does municipal solid waste generation in China support the Environmental Kuznets Curve? New evidence from spatial linkage analysis. *Waste Management*, *84*, 310–319. Retrieved from https://doi.org/10.1016/j.wasman.2018.12.006

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: A Review of the Literature. *Economics of Disasters and Climate Change*, *4*(1), 223–247. Retrieved from https://doi.org/10.1007/s41885-020-00060-5

Hassan, S. A., Zaman, K., & Gul, S. (2015). The Relationship between Growth-Inequality-Poverty Triangle and Environmental Degradation: Unveiling the Reality. *Arab Economic and Business Journal*, *10*(1), 57–71. Retrieved from https://doi.org/10.1016/j.aebj.2014.05.007

Ilham, A. P., Sri, M., & Sasongko (2023). The Effect of Natural Disaster on Regional Economic Growth, Unemployment, Poverty, and Human Development Index in Thirty Indonesian Provinces. *Journal of Indonesian Applied Economics*, *11*(1), 40-59. Retrieved from https://jiae.ub.ac.id/index.php/jiae/article/download/1196/244

Karim, A., & Noy, I. (2016a). Poverty and Natural Disasters - A Qualitative Survey of the Empirical Literature. *The Singapore Economic Review*, *61*(01), 1640001. Retrieved from https://doi.org/10.1142/S0217590816400014

Karim, A., & Noy, I. (2016b). Poverty and Natural Disasters: A Regression Meta-Analysis. *Review of Economics and Institutions*, *7*(2), 26. Retrieved from https://doi.org/10.5202/rei.v7i2.222

Kawasaki, A., Kawamura, G., & Zin, W. W. (2020). A local level relationship between floods and poverty: A case in Myanmar. *International Journal of Disaster Risk Reduction*, *42*, 101348. Retrieved from https://doi.org/10.1016/j.ijdrr.2019.101348

Keerthiratne, S., & Tol, R. S. J. (2018). Impact of natural disasters on income inequality in Sri Lanka. *World Development*, *105,* 217–230. Retrieved from https://doi.org/10.1016/j.worlddev.2018.01.001

Khan, A., Bibi, S., Ardito, L., Lyu, J., Hayat, H., & Arif, A. (2020). Revisiting the Dynamics of Tourism, Economic Growth, and Environmental Pollutants in the Emerging Economies—Sustainable Tourism Policy Implications. *Sustainability*, *12*(6), 2533. Retrieved from https://doi.org/10.3390/su12062533

Khan, A., Bibi, S., Lyu, J., Latif, A., & Lorenzo, A. (2021). COVID-19 and sectoral employment trends: assessing resilience in the US leisure and hospitality industry. *Current Issues in Tourism*, *24*(7), 952–969. Retrieved from https://doi.org/10.1080/13683500.2020.1850653

Kim, H., & Marcouiller, D. W. (2015). Considering disaster vulnerability and resiliency: the case of hurricane effects on tourism-based economies. *The Annals of Regional Science*, *54*(3), 945–971. Retrieved from https://doi.org/10.1007/s00168-015-0707-8

Kim, S. J., Park, S., Lee, S. J., Shaimerdenova, A., Kim, J., Park, E., Lee, W., Kim, G. S., Kim, N., Kim, T. H., Lim, C.-H., Choi, Y., & Lee, W.-K. (2021). Developing spatial agricultural drought risk index with controllable geo-spatial indicators: A case study for South Korea and Kazakhstan. *International Journal of Disaster Risk Reduction*, *54*, 102056. Retrieved from https://doi.org/10.1016/j.ijdrr.2021.102056

Lee, C. -Y., & Tang, C. F. (2019). How Do Natural Disasters Influence the Rate of Poverty? *Journal of Poverty*, *23*(6), 478–486. Retrieved from https://doi.org/10.1080/10875549.2019.1616033

Lee, J., & Wong, D. W. S. (2001). *Statistical analysis with ArcView GIS*. Hoboken, N, J.: John Wiley.

Leichenko, R., & Silva, J. A. (2014). Climate change and poverty: vulnerability, impacts, and alleviation strategies. *WIREs Climate Change*, *5*(4), 539–556. Retrieved from https://doi.org/10.1002/wcc.287

Li, M., Lv, J., Chen, X., & Jiang, N. (2015). Provincial evaluation of vulnerability to geological disaster in China and its influencing factors: a three-stage DEA-based analysis. *Natural Hazards*, *79*(3), 1649–1662. Retrieved from https://doi.org/10.1007/s11069-015-1917-1

Marfuah, M., Cempaka, S., Risdan Ardiansyah, A., Rahmawati, L., Yunia Rediana, M., & Koswara, R. (2021). Kebijakan Pemerintah dalam Penanggulangan Bencana di Indonesia. *Jurnal Studi Ilmu Sosial dan Politik*, *1*(1), 35–45. Retrieved from https://doi.org/10.35912/jasispol.v1i1.184

McMahon, M. M. (2007). Disasters and Poverty. *Disaster Management and Response*, *5*(4), 95–97. Retrieved from https://doi.org/10.1016/j.dmr.2007.09.001

Menendez, M. (2014). Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia. *Journal of Development Economics, 118*(33), 1–44. Retrieved from http://doi.org/10.1016/j.jdeveco.2015. 08.004

Miljkovic, T., & Miljkovic, D. (2014). Modeling Impact of Hurricane Damages on Income Distribution in the Coastal U.S. *International Journal of Disaster Risk Science*, *5*(4), 265–273. Retrieved from https://doi.org/10.1007/s13753-014-0030-5

Moran, P. A. P. (1948). The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society: Series B (Methodological)*, *10*(2), 243–251. Retrieved from https://doi.org/10.1111/j.2517-6161.1948.tb00012.x

Natural Disaster Management Statistics. (2020). testimony of Natural Disaster Management Agency. Retrieved from https://www.undrr.org/media/48530/download

Nepal, S., Tripathi, S., & Adhikari, H. (2021). Geospatial approach to the risk assessment of climate-induced disasters (drought and erosion) and impacts on out-migration in Nepal. *International Journal of Disaster Risk Reduction*, *59*, 102241. Retrieved from https://www.undrr.org/media/48530/download

Ngoran, S. D., Yvette, B., Ngoran, B. S., & Xue, X. (2015). Circumscribing the nexus between natural disaster, water resources and poverty in Sub-Saharan Africa. *Journal of Resource Development and Management*, *7*, 31-40. Retrieved from https://www.academia.edu/download/87828490/234696057.pdf

Noy, I. (2009). The Macroeconomic Consequences of Disasters. *Journal of Development Economics* *88*(2), 221–231. Retrieved from https://doi.org/10.1016/j.jdeveco.2008.02.005.

Olopade, B. C., Okodua, H., Oladosun, M., & Asaleye, A. J. (2019). Human capital and poverty reduction in OPEC member countries. *Heliyon*, *5*(8), e02279. Retrieved from https://doi.org/10.1016/j.heliyon.2019.e02279

Ouchen, A., & Montargot, N. (2021). Non-spatial and spatial econometric analysis of tourism demand in a panel of countries around the world. *Spatial Economic Analysis*, 1–22. Retrieved from https://doi.org/10.1080/17421772.2021.1940256

Padli, J., & Habibullah, M. S. (2009). Natural Disaster Death and Socio-Economic Factors in Selected Asian Countries: A Panel Analysis. *Asian Social Science*, *5*(4), p65. Retrieved from https://doi.org/10.5539/ass.v5n4p65

Padli, J., Habibullah, M. S., & Baharom, A. H. (2018). The impact of human development on natural disaster fatalities and damage: panel data evidence. *Economic Research-Ekonomska Istraživanja*, *31*(1), 1557–1573. Retrieved from https://doi.org/10.1080/1331677X.2018.1504689

Pathak, S., & Olmo, J. C. (2021). Analysing spatial interdependence among the 2011 Thailand flood-affected small and medium enterprises for reduction of disaster recovery time period. *Geoenvironmental Disasters*, *8*(1), 8. Retrieved from https://doi.org/10.1186/s40677-021-00180-4

Putra, H. S. (2017). Natural disasters and poverty in Indonesia. *Journal of Administrative Transformation*, *1*, 1420–1431.

Romão, J., & Saito, H. (2017). A spatial analysis of the determinants of tourism performance in Japanese Prefectures. *Asia-Pacific Journal of Regional Science*, *1*(1), 243–264. Retrieved from https://doi.org/10.1007/s41685-017-0038-0

Rosalia, A. C. T. S., & Hakim, L. (2021). Spatial Analysis of the Impact of Flood and Drought on Food Security Index. *Nature Environment and Pollution Technology*, *20*(2), 721-727. Retrieved from https://doi.org/10.46488/NEPT.2021.v20i02.031

Rush, J. V. (2018). The impact of natural disasters on education in Indonesia. *Economics of Disasters and Climate Change*, *2*, 137-158. Retrieved from https://link.springer.com/article/10.1007/s41885-017-0022-1

Sawada, Y. (2017). Disasters, Household Decisions, and Insurance Mechanisms: A Review of Evidence and a Case Study from a Developing Country in Asia: Disasters and Households: A Review and A Case. *Asian Economic Policy Review*, *12*(1), 18–40. Retrieved from https://doi.org/10.1111/aepr.12154

Sawada, Y., & Takasaki, Y. (2017). Natural Disaster, Poverty, and Development: An Introduction. *World Development*, *94*, 2–15. Retrieved from https://doi.org/10.1016/j.worlddev.2016.12.035

Scheidel, W. (2017). *The great leveler: violence and the history of inequality from the Stone Age to the twenty-first century*. Princeton: Princeton University Press. Retrieved from https://www.tandfonline.com/doi/full/10.1080/14616696.2019.1610786

Siburian, M. E. (2022). The link between fiscal decentralization and poverty – Evidence from Indonesia. *Journal of Asian Economics*, *81*, 101493. Retrieved from https://doi.org/10.1016/j.asieco.2022.101493

Smiley, K. T., Howell, J., & Elliott, J. R. (2018). Disasters, local organizations, and poverty in the USA, 1998 to 2015. *Population and Environment*, *40*(2), 115–135. Retrieved from https://doi.org/10.1007/s11111-018-0304-8

Songwathana, K. (2018). The Relationship between Natural Disaster and Economic Development: A Panel Data Analysis. *Procedia Engineering*, *212*, 1068–1074. Retrieved from https://doi.org/10.1016/j.proeng.2018.01.138

Sun, Y., Yang, Q., & Chen, P. (2018). A Study of Spatial Evolution Patterns of Tourist Destinations Disaster Risks. *Journal of Risk Analysis and Crisis Response*, *8*(1), 35. Retrieved from https://doi.org/10.2991/jrarc.2018.8.1.4

Tasri, E. S., Karimi, K., & Muslim, I. (2022). The effect of economic variables on natural disasters and the impact of disasters on economic variables. *Heliyon*, *8*(1), e08678. Retrieved from https://doi.org/10.1016/j.heliyon.2021.e08678

Teixeira, P. N. (2014). Gary Becker's early work on human capital – collaborations and distinctiveness. *IZA Journal of Labor Economics*, *3*(1), 12. Retrieved from https://doi.org/10.1186/s40172-014-0012-2

Tselios, V., & Tompkins, E. L. (2019). What causes nations to recover from disasters? An inquiry into the role of wealth, income inequality, and social welfare provisioning. *International Journal of Disaster Risk Reduction*, *33*, 162–180. Retrieved from https://doi.org/10.1016/j.ijdrr.2018.10.003

Todaro, M. P., & Smith, S. C. (2012). *Economic Development* (11th Ed.). New York: Addison Wesley.

Wang, K., Zhu, Y., & Zhang, J. (2021). Decoupling economic development from municipal solid waste generation in China's cities: Assessment and prediction based on the Tapio method and EKC models. *Waste Management*, *133*, 37–48. Retrieved from https://doi.org/10.1016/j.wasman.2021.07.034

Warr, P., & Aung, L. L. (2019). Poverty and inequality impact of a natural disaster: Myanmar's 2008 cyclone Nargis. *World Development*, *122*, 446–461. Retrieved from https://doi.org/10.1016/j.worlddev.2019.05.016

Winsemius, H. C., Jongman, B., Veldkamp, T. I. E., Hallegatte, S., Bangalore, M., & Ward, P. J. (2018). Disaster risk, climate change, and poverty: assessing the global exposure of poor people to floods and droughts. *Environment and Development Economics*, *23*(3), 328–348. Retrieved from https://doi.org/10.1017/S1355770X17000444

World Bank. (2019). *Strengthening The Disaster Resilience of Indonesian Cities - A Policy Note*. Retrieved from https://documents1.worldbank.org/curated/en/748581569515561529/pdf/Strengthening-the-Disaster-Resilience-of-Indonesian-Cities-A-Policy-Note.pdf

Xiang, M., Duan, L., Wei, F., Yang, J., Li, W., Wang, C., Yang, W., & Deng, Q. (2022). Analysis on the spatial differentiation characteristics of poverty risk caused by disaster under the stress of geological disasters: a case study of Sichuan Province. *Environmental Science and Pollution Research*, *29*(34), 52111-52122. Retrieved from https://link.springer.com/article/10.1007/s11356-022-19485-4

Yang, Y., & Wong, K. K. F. (2012). A Spatial Econometric Approach to Model Spillover Effects in Tourism Flows. *Journal of Travel Research*, *51*(6), 768–778. Retrieved from https://doi.org/10.1177/0047287512437855

Xiao, Y., dan Nilawar, U. (2013). Winners and losers: Analysing post-disaster spatial economic demand shift. Disasters, 37(4), 646–668. Retrieved from http://doi.org/10.1111/disa.12025

Zhou, K., Wu, J., & Liu, H. (2021). Spatio-temporal estimation of the anthropogenic environmental stress intensity in the Three-River-Source National Park region, China. *Journal of Cleaner Production*, *318*, 128476. Retrieved from https://doi.org/10.1016/j.jclepro.2021.128476

Cite this article: Hidayati, N. A., Kusumawardani, D., Rahmawati, Y., Martina, A., Agusti, K. S., Amalia, Y. Y., & Ramdaniyah, N. F. (2025). Spatial Linkage between Natural Disaster and Poverty on the Archipelago Country (Case Study: Indonesia). *Iranian Economic Review*, *29*(3), 841-867.