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DO FLOODS LEAVE LASTING SCARS? LONG-TERM EFFECT OF FLOOD EVENTS ON INDONESIA'S REGIONAL ECONOMY

Amesta Kartika Ramadhani*, Sephia Dwi Astuti, Ashtian Ultanti, Anggi Rahajeng, Fatima Putri Prativi
Department of Economics and Business, Vocational School, Universitas Gadjah Mada, Yogyakarta, Indonesia
*Corresponding author: amesta.kartika.r@ugm.ac.id

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ABSTRACT

As climate-related disasters increase in intensity and frequency, Indonesia is becoming more vulnerable to their impacts. Among these disasters, flooding is one of the most threatening hazards, causing both short and long-term economic consequences. While existing literature reports the impact of a single event, the impact of disaster on economic performance or immediate impact of disaster, the dynamic impacts on both GRDP per capita and inequality remain underexplored. To address this research gap, this study analyzes the economic impacts of floods using a Panel Autoregressive Distributed Lag (P-ARDL) model. It examines how floods affect GRDP per capita and inequality levels in both short and long run. The analysis also incorporates other explanatory variables, including Foreign Direct Investment (FDI), Domestic Investment (DDI), the Human Development Index (HDI), and population size. The results indicate that, in the long run, floods have a negative effect on GRDP per capita; a 1% increase in flood events reduces GRDP per capita by 0.48%. In the short term, every 1% increase in flood frequency is associated with a 0.013% reduction in per capita GRDP. This study also reveals that floods have a significant negative impact on income inequality in both the short and long term. However, this paradoxical finding needs careful interpretation. It may not indicate an increase in social welfare but rather reflects the impact of flooding on wealthier groups, potentially narrowing the gap. Further research is needed to confirm this. This research underscores the importance of improving flood mitigation to maximize flood prevention and strengthen the resilience of economic productivity. Furthermore, the research findings need to be further explored, including the mechanisms by which floods reduce per capita GRDP and explore how floods can reduce inequality.

1. INTRODUCTION

Disasters are a global challenge that can hinder development. According to the EM-DAT publication, 10,257 natural disasters occurred worldwide between 2000 and 2024 (*EM-DAT - The International Disaster Database*, 2024.). Of these, 7,202 occurred in developing countries, causing losses of USD 1.48 trillion, or one-third of total global disaster (World Bank, 2020). The United Nations (2025) estimates that by 2030, the world will experience approximately 560 disaster events in a year, equivalent to 1.5 events per day. Furthermore, nearly 50% of the global population residing in coastal areas will be exposed to hazards such as floods, storms, and tsunamis.

Disasters can impose both positive and negative consequences for a country's economic condition, depending on their level of development or the disaster's specific characteristics. In Noy & Nualsri (2007)), the neoclassical framework predicts that disasters are exogenous shocks, which cause damage to physical and human capital. Consequently, it will further result in faster capital accumulation and cause temporary higher growth until a stable economic state occurs. However, their research shows that negative shocks from disasters to human capital cause a decrease in the growth rate, while those on physical capital have no significant long-term impact. Previous studies support that disasters can reduce economic growth and GDP per capita (A. Khan et al., 2020) for instance, Huang et al. (2024) found that moderate and strong earthquakes in China caused a long-term decline in per capita GRDP due to their extensive damage. Some literatures introduced the concept of "creative destruction", where disasters stimulate economic growth through reinvestment dan improvement of capital goods, such as transportation network, therefore, disasters may be beneficial in improving long-term growth (Noy & Nualsri, 2007). However, this phenomenon is usually observed after extreme or catastrophic natural events (Hallegatte & Dumas, 2009; Zhou & Zhang, 2021a), rather than a recurrent and high-frequency event such as floods. Recurring disasters can also potentially disrupt economic stability without requiring the same amount of capital investment to recover from a single catastrophe. Recurring disasters can also potentially disrupt economic stability without requiring the same amount of capital investment to recover from a single catastrophe.

Floods are among the most common hydrometeorological disasters and possess significant potential cause for economic losses. Empirical evidence on the impact of floods on economic conditions is highly context-dependent, varying across regions, and time. They influence economic performance through several mechanisms, including damage to public infrastructure (Ashizawa et al., 2022), the disruption of transportation networks (Ding, 2013), and a decline in productivity (Hu et al., 2019; Loayza et al., 2012). In Japan, Ashizawa et al. (2022) found that GDP would be affected more significantly, by up to 16.3% when flood damaged public infrastructure such as roads and power supplies, compared to only a 0.32% decrease in GDP resulting from damage to household assets alone. Raddatz (2009) found that severe hydrometeorological disasters can reduce GDP per capita by about 0.6 percent following a single event. Similarly, Shabnam (2014), using panel data from 187 countries over the period 1960–2010, found that floods significantly decrease per capita GRDP growth, with every 1,000 people affected leading to a 0.005 percent decline. In the short term, floods reduce economic inputs and outputs because of damaged facilities and infrastructure, the degradation of agricultural land, and disruption in mobility caused by floodwater. In the long term, however, the economic consequences of floods are quite complex. Floods can both hinder and stimulate economic growth, leaving room for further examination. In India, Parida & Prasad Dash (2020) observed that, in the long run, a 10 percent increase in flood-related losses, affected population, and inundated area leads to a decline in per capita GDP growth by 0.03, 0.06, and 0.02 percent, respectively.

Beyond economic metrics, disasters also disproportionately impact vulnerable groups. According to (Bangalore et al., 2017), this uneven impact occurs due to several mechanisms. First, vulnerable groups suffer overexposure to hazards, such as living in vulnerable areas. Second, they have higher vulnerability, so when affected by disasters, the losses they suffer are two to three times greater than those experienced by the wealthier groups. Third, they are lacking in the ability to cope and recover due to limited social protection. Fourth, they may suffer education and health impact, such as children withdrawing from school. Educational disruption, often caused by diminished capacity to finance education post-disaster, can lead to long-term impacts (Vin et al., 2025). By disrupting livelihoods and human capital, disasters do not only shock the economy but also exacerbate the existing inequalities (Parvin et al., 2016; Silva Araújo et al., 2022; Tovar Reaños, 2021).

This study aims to analyze the impact of flooding on Indonesia's economic conditions using data from 34 provinces over the period 2014–2024. Indonesia is highly susceptible to hydrometeorological events, particularly floods and drought. Indonesia's National Disaster Management Office (BNPB) recorded an increasing trend in these incidents during 2010-2024, with 2021 marking the highest frequency of occurrence (BNPB, 2025). Over the past 25 years, the provinces of Central Java, West Java, East Java, Aceh, and South Sulawesi have seen the highest accumulation of such disasters. Notably, flood events remained consistently high, with 1,794 events recorded in 2021, 1,531 events in 2022, and 1,519 in 2020 (BNPB, 2024). This persistent frequency reflects higher risk, both in terms of human casualties and economic losses (Budiyono et al., 2015; Surminski et al., 2015).

This research positions iself within the unresolved debate of the economic impact of disaster by addressing gap on the lack of long-term analysis on how reccurrent hazards disrupt economy and inequality in developing economies. It contributes to existing literature in three primary ways. First, it provides new empirical evidence on the relationship between high-frequency nature of flood events and economic performance. Second, this study examines the impact dynamics of disasters by employing a Panel Autoregressive Distributed Lag (P-ARDL) using panel data at provincial level. While most existing studies focus on immidiate effect, research examining long-term consequences remains limited (Berlemann & Wenzel, 2018; Krichene et al., 2021), therefore this research intends to distinguish the short-term and long-term impacts on GRDP per capita and inequality. Third, it evaluates the inequality transmision mechanisms by testing the impact of floods on the Gini ratio.

In summary, this study analyzes the impact of flooding on Indonesia's regional economy, focusing on gross regional domestic product (GRDP) and inequality (Gini ratio), both in the short and long term. The findings are expected to contribute fresh empirical evidence to the field of disaster economics and provide a foundation for policy formulation aimed at enhancing economic resilience in flood-prone regions.

2. RESEARCH METHODS

This study examines the impact of flooding on per capita GRDP and income inequality across 34 provinces in Indonesia over the period 2014–2024. Although Indonesia has changed its administrative regions from 34 to 38 provinces during this period, due to limited data availability for the newly established provinces, this study uses data from 34 provinces. The data were obtained from secondary sources published by Statistics Indonesia (BPS) and the Indonesian Disaster Information and Data (DIBI) of the National Disaster Management Agency (BNPB).

Table 1 reflects the operational definitions of variables along with their descriptive statistics. This study incorporates additional explanatory variables that are expected to influence both per capita GRDP and income inequality. Given that economic growth and inequality are multifactorial and complex, several explanatory variables are included to mitigate bias.

The explanatory variables associated with per capita GRDP include Foreign Direct Investment (FDI), government spending, and the Human Development Index (HDI). FDI is widely recognized as a catalyst for economic growth, as it encourages capital accumulation and creates jobs, which in turn increase labor productivity (Borensztein et al., 1998). Furthermore, FDI contributes positively towards GRDP through technology transfer, the expansion of Research and Development (R&D) capacity, and improvement in marketing sttrategies (Fahruddin, 2021). Government spending, on the other hand, is identified as a policy tool to influence economic growth and short-term output fluctuations (Sudarsono, 2015).

Additionally, the quality of human resources, as represented by the Human Development Index (HDI) is one of the fundamental drivers in economic growth along with increasing opportunities caused by increasing level of human development (Elistia & Syahzuni, 2018).

Meanwhile, explanatory variables for income inequality include population growth and GRDP growth. Population growth is often associated with increased inequality. As suggested by Ram (1984), a 1% decrease in population growth is associated with an increase in the income share of the poor, thus reducing inequality. In the context of poor and developing countries, rapid population growth is often not matched by sufficient employment opportunities, therefore, it may risk increasing inequality. Furthermore, the relationship between GRDP growth and inequality remains a debate. Alamanda (2021) found that increasing GDP growth in 50 countries raising the Gini Index by 0.082 – 0.085 points. On the other hand, Majumdar & Partridge (2009) suggest that economic growth will reduce inequality by increasing access to jobs and income.

Table 1. Variables and Descriptive Statistic of Variables

Variable	Operational Definisions	Source	Mean	Min	Max	Std. Dev
GRDP_Cap	GRDP per capita (million Rupiah)	BPS	43,626.4	10,741.3	201.315,1	33,911.2
Inequality	Gini index (0-1)	BPS	0.354300	0.24	0.45	0.041400
Flood_Numb	The frequency of flood accident	DIBI BNPB	32.43208	0	256	39.15142
Flood_Loss	Economic loss (Rupiah)	BPS	37,228.5	20	1,272,312	92,876.9
FDI	Foreign Direct Investment (million US$)	BPS	958,521	895.7	8,283,746	1,416,41
Gov_Spend	Government spending (trillion Rupiah)	BPS	3.25e+13	4.85e+12	1.46e+14	2.91e+13
HDI	Human Development Index (0-100)	BPS	70.73267	56.75	83.08	4.187427
Pop_Growth	Population growth (%)	BPS	1.57999	-0.52229	3.94	0.608670
Ec_Growth	GRDP growth (%)	BPS	4.692567	-15.74	22.94	3.493968

Source: Processed Data

This study employs the Panel ARDL (P-ARDL) approach, developed by (Pesaran et al., 2001), to simultaneously estimate the short-run and long-run effects. It is interesting to examine the impacts over different time periods to determine whether there are differences between the long-term and short-term impacts of flooding, and which of the two is more significant. P-ARDL allows for estimating short-term fluctuations and long-run equilibrium to understand how flood impacts can shift to long-term impacts. To systematically capture these impacts, the analysis is structured into two models: the first examines the impact of flooding on per capita GRDP (Equation 1), followed by the second model, which explores its effect on inequality (Equation 2).

The first model examines the impact of flood disasters on GRDP per capita, with all variables including GRDP per capita, foreign direct investment (FDI), government spending, and the Human Development Index (HDI) transformed into their natural logarithmic forms. This specification is adopted based on the baseline model in levels, where the error correction term (ECM) is negative but statistically insignificant. Although the negative coefficient indicates short-run adjustment toward equilibrium, its lack of significance implies a slow speed of convergence and a weak long-run relationship among the variables.

The use of logarithmic transformation is well established in econometric analysis, particularly in macroeconomic modeling, as it helps stabilize variance, reduce heteroskedasticity, and improve statistical efficiency. It also facilitates interpretation in terms of elasticities and mitigates scale differences across variables (Manning, 1998; West, 2022). Accordingly, the logarithmic specification provides more robust and economically interpretable estimates of both short-run dynamics and long-run relationships.

For the second model, which analyzes the impact of flood disasters on income inequality as proxied by the Gini index, the estimation results are obtained without logarithmic transformation. The estimated ECM is negative and statistically significant, indicating the presence of a valid error-correction mechanism in which short-run disequilibria adjust toward long-run equilibrium. This outcome may be associated with the relatively lower dispersion of both the dependent variable and the explanatory variables such as population growth and economic growth, whose distributions exhibit less variability than those in the first model. Consequently, the second model yields more stable and reliable estimates.

$$\Delta\log\_GRDPCap_{(it)} = \pi_0 + \sum_{k=1}^{n}\beta_{1k}\ \Delta\log\_GRDPCap_{(it-k)} + \sum_{k=0}^{n}\beta_{2k}\ \Delta\log\_floodnumb_{(it-k)} + \sum_{k=1}^{n}\beta_{3k}\ \Delta\log\_FDI_{(it-k)} + \sum_{k=1}^{n}\beta_{4k}\ \Delta govspend_{(it-k)} + \sum_{k=1}^{n}\beta_{5k}\ \Delta log\_HDI_{(it-k)} + \pi_1 log\_GRDPCap_{(it-1)} + \pi_2 log\_floodnumb_{(it-1)} + \pi_3 log\_FDI_{(it-1)} + \pi_4 log\_govspend_{(it-1)} + \pi_5 log\_HDI_{(it-1)} + \lambda ECM_{(it-1)} + \varepsilon_{(it)} \ldots\ldots\ldots\ldots (1)$$

$$\Delta Gini_{(it)} = \pi_0 + \sum_{k=1}^{n}\beta_{1k}\ \Delta Gini_{(it-k)} + \sum_{k=0}^{n}\beta_{2k}\ \Delta Floodnumb_{(it-k)} + \sum_{k=1}^{n}\beta_{3k}\ \Delta Pop\_Growth_{(it-k)} + \sum_{k=1}^{n}\beta_{4k}\ \Delta Ec\_Growth_{(it-k)} + \pi_1 Gini_{(it-1)} + \pi_2 Floodnumb_{(it-1)} + \pi_3 Pop\_Growth_{(it-1)} + \pi_4 Ec\_Growth_{(it-1)} + \lambda ECM_{(it-1)} + \varepsilon_{(it)} \ldots. (2)$$

Whereas:

Δ	Change in data for example, $\Delta log\_GRDPCap_{(it)} = log\_GRDPCap_{(t)} - log\_GRDPCap_{(t-1)}$
log_GRDPCap	GRDP per capita in natural logarithm
floodnumb	The number of flood event
log_floodnumb	The number of flood events in natural logarithm
log_FDI	Foreign Direct Investment in natural logarithm
log_govspend	Government expenditure in natural logarithm
log_HDI	Human Development Index in natural logarithm
Pop_Growth	Population growth
Ec_Growth	Economic growth
π_0	Intercept
β_1k, β_2k, β_3k, β_4k, β_5k	Short-run relationship coefficient for each variable
λ	Error correction term (ECM), which indicates the speed of adjustment towards long-run equilibrium. The λ value is expected to be negative and significant, indicating the existence of long-run equilibrium.
$ECM_{(it-1)}$	Error Correction Model from the previous period, describing the difference between the actual value and the long-run value
ε	Error term
i	Unit cross-section (province)
t	Time period
it – k	Indicates the value of the variable for the i unit at t time minus k. For example, if k=1, it represents the previous one-period lag. This is used to capture the lagged effect in the short run.

The analytical procedure employing the P-ARDL method is illustrated in Figure 1. It begins with the preprocessing of panel data. Subsequently, a stationarity test is performed using the Im–Pesaran–Shin (IPS) method to determine the integration order of each variable and to confirm that no variable is integrated beyond I(1). If the results indicate a combination of variables that are stationary at level I(0) and at first difference I(1), the P-ARDL approach is suitable.

The next step involves conducting a cointegration test using the Kao and Pedroni methods to identify the presence of long-run relationships among variables. Once cointegration is verified, the P-ARDL model is estimated using two approaches, Pooled Mean Group (PMG) and Dynamic Fixed Effect (DFE) which enable simultaneous analysis of short-run and long-run dynamics. The Mean Group (MG) model could not be estimated due to the limited number of observed years.

In the end, the optimal model was selected using the Hausman test, which determines the most appropriate estimation approach based on whether relationships across observation units are homogeneous or heterogeneous. The selected model then served as the basis for interpreting the short-run and long-run relationships in this study.

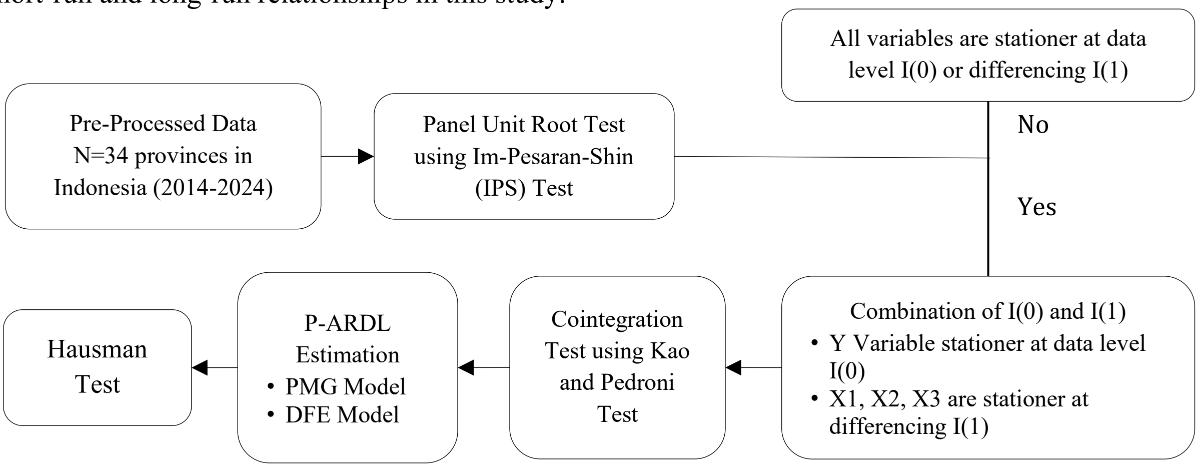

Figure 1. Analytical Procedure

3. RESULTS AND DISCUSSION

3.1. RESULT

Hydrometeorological disasters are events triggered by climate and weather phenomena. These include floods, droughts, storms, or extreme weather events. Due to its complex geographical and climatological conditions, Indonesia is highly susceptible to these disasters. According to the Indonesian Disaster Information Data (DIBI) published by BNPB (2025), the intensity and frequency of such events in Indonesia have continued to rise over time. In 2021 alone, the total number of hydrometeorological disasters reached 5,287 events, representing the increasing threat of climate risks. Among these hazards, floods remain the most frequent type of hydrometeorological disaster in Indonesia (BNPB, 2025). In the last ten years, Indonesia has experienced a rising trend in the number of hydrometeorological disasters (Figure 2).

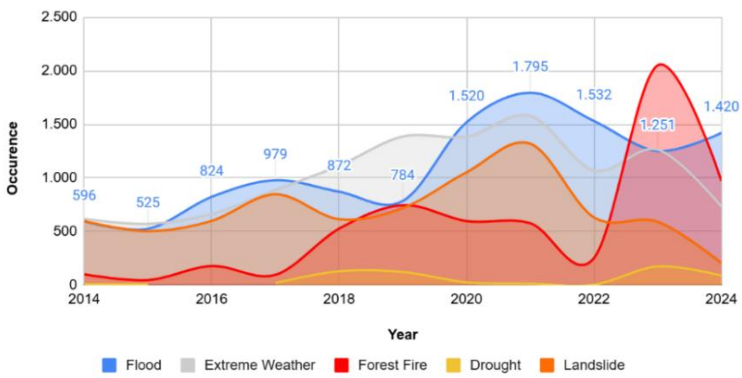

Figure 2. Hydrometeorological Disaster Occurrence in Indonesia (2010-2024)

Source: DIBI BNPB

The spatial distribution of floods in 2024 (Figure 3) reveals a disparity between the frequency and its human impact. North Sumatra, West Java, East Java, and South Sulawesi Province recorded the highest frequency of floods, with between 86 and 144 events. However, Central Java Province experienced the largest number of people affected by floods, reaching 927,265 individuals, followed by South Sulawesi with 750,031. Interestingly, despite recording the highest number of flood incidents (144 events), West Java had fewer people affected (468,870 individuals), compared to Central Java, which experienced only 80 flood events but nearly double the number of victimes. This finding indicates that the severity of human impacts is not determined only by the frequency of occurrences. Instead, it is potentially influenced by regional differences in exposure, population density, and socio-economic vulnerability. This suggests that regions with higher levels of vulnerability may experience higher impacts, even from fewer disaster events.

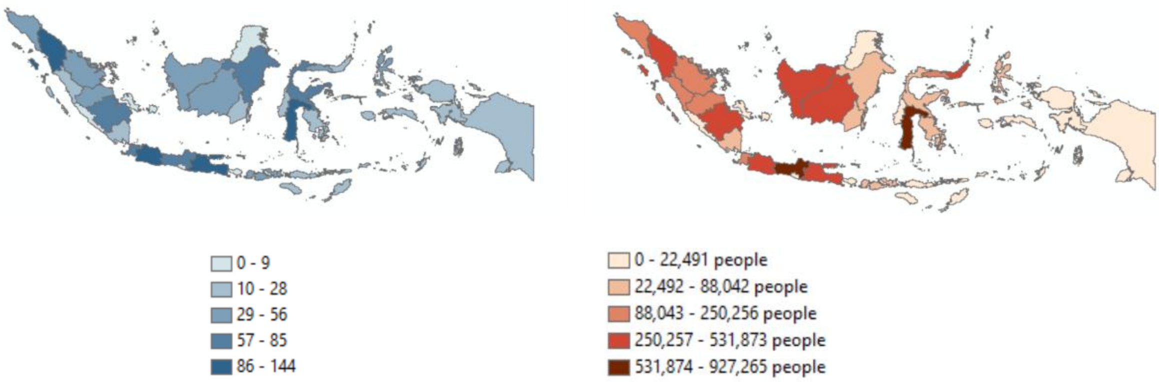

Figure 3. Number of Floods and Number of People Affected by Floods (2024)
Source: DIBI BNPB (2024)

The first model examines the impact of flood disasters on GRDP per capita, with GRDP per capita (log_GRDPCap) specified as the dependent variable. Following data pre-processing, a panel unit root test is performed using the Im–Pesaran–Shin (IPS) approach (Table 2). The results indicate that GRDP per capita (log_GRDPCap) and the Human Development Index (log_HDI) are non-stationary at levels but become stationary after first differencing, implying that both variables are integrated of order one, I(1). In contrast, the null hypothesis of a unit root is rejected at levels for flood frequency (log_FloodNumb), foreign direct investment (log_FDI), and government spending (log_GovSpend), indicating that these variables are stationary and integrated of order zero, I(0).

The presence of variables integrated at mixed orders, I(0) and I(1), constrains the use of conventional cointegration techniques. Under these conditions, the Panel Autoregressive Distributed Lag (P-ARDL) model is appropriate, as it allows for the estimation of both short-run dynamics and long-run relationships without requiring all variables to be integrated at the same order, provided that none is integrated beyond I(1).

Table 2. IPS Panel Unit Root Test Results for the Flood Impact Model on GRDP per Capita

Variable	IPS Test *(Z-tiddle-bar)*		P-value		Decision
	Level	1st diff.	Level	1st diff.	
log_GRDPCap	5.6572	-5.7320***	1.000	0.000	I(1)
log_floodnumb	-4.0486***	-8.0271 ***	0.000	0.000	I(0)
log_FDI	-3.8378***	-6.5560***	0.001	0.000	I(0)
log_govspend	-2.9226***	-5.6897***	0.002	0.000	I(0)
log_HDI	5.4467	-4.3046***	1.000	0.000	I(1)

The second model examines the effect of flood frequency on income inequality (Table 3). Based on the Im–Pesaran–Shin (IPS) test, the Gini index and population growth (Pop_Growth) are found to be integrated of order one, I(1), whereas flood frequency (Flood_Numb) and economic growth (Ec_Growth) are integrated of order zero, I(0).

The presence of variables with mixed orders of integration justifies the use of the Panel Autoregressive Distributed Lag (PARDL) approach. This method enables the estimation of both short-run and long-run relationships under such conditions, provided that no variable is integrated beyond I(1). Accordingly, the PARDL model is employed in this study.

Table 3 IPS Panel Unit Root Test Results for the Flood Impact Model on Inequality

Variable	IPS Test *(Z-tiddle-bar)*		P-value		Decision
	Level	1st diff.	Level	1st diff.	
Inequality	-0.8115	-8.7736***	0.2085	0.000	I(1)
Flood_Numb	-3.1573***	-8.2471***	0.008	0.000	I(0)
Pop_Growth	1.2693	-7.5347***	0.8978	0.000	I(1)
Ec_Growth	-5.2487***	-8.0411 ***	0.0000	0.000	I(0)

To assess the existence of a long-run equilibrium relationship among the variables, panel cointegration tests are conducted using the Kao and Pedroni approaches (Table 4.). From the first model, the Kao test results indicate significance in the unadjusted modified Dickey–Fuller t and unadjusted Dickey–Fuller t statistics, but not in the other three test types. Meanwhile, all three statistics under the Pedroni test were significant at 5% , leading to the rejection of the null hypothesis of no cointegration. Therefore, it can be concluded that the overall model satisfies the cointegration requirement.

The presence of cointegration indicates that the variables share a stable long-run relationship, despite short-term deviations. This implies that any disequilibrium in the short run will gradually adjust toward the long-run equilibrium. Given this condition, the Panel Autoregressive Distributed Lag (P-ARDL) model is particularly appropriate, as it incorporates both long-run equilibrium estimation and short-run dynamics through an error correction mechanism.

Table 4. Cointegration Test using Kao and Pedroni Test Result for the Flood Impact Model on GRDP per Capita

	Kao Test			Pedroni Test	
	Stat.	P-value		Stat.	P-value
Modified Dicky Fuller t	-1.2759	0.1010	Modified Philips Perron	6.4893	0.000***
Dicky-Fuller t	-1.2807	0.1002	Phillips-Perron t	-5.9571	0.000***
Augmented Dicky- Fuller t	-0.4839	0.3142	Augmented Dicky-Fuller t	-8.8181	0.000***
Unadjusted modified Dicky-Fuller t	-2.7741	0.0028***			
Unadjusted Dicky-Fuller t	-2.1457	0.0159***			

For the second model, the a cointegration test is performed to assess whether a long-run equilibrium relationship exists among the variables. This procedure is essential to validate long-run estimations, particularly when some variables are not stationary at the level (Table 5).

Conducting a cointegration test also helps prevent the occurrence of spurious regression results. In this study, both the Kao and Pedroni cointegration tests are applied to confirm the presence of a long-run relationship.

Table 5. Cointegration Test using Kao and Pedroni Test Result for The Flood Impact Model on Inequality

	Kao Test			Pedroni Test	
	Stat.	P-value		Stat.	P-value
Modified Dicky Fuller t	1.5126	0.0652	Modified Philips Perron	5.0881	0.000***
Dicky-Fuller t	-0.98244	0.1630	Phillips-Perron t	-13.6101	0.0008***
Augmented Dicky- Fuller t	2.8061	0.0025***	Augmented Dicky-Fuller t	-8.8923	0.0008***
Unadjusted modified Dicky-Fuller t	-3.4396	0.0003***			
Unadjusted Dicky-Fuller t	-4.7476	0.000***			

After establishing the presence of cointegration, the appropriate lag structure of the model must be specified to properly capture the dynamic adjustment process among variables (Table 6). The optimal lag length is determined based on ARDL lag selection results across provinces. Given the relatively short time dimension of the dataset (2014–2024, T = 11), the maximum lag length is restricted to one to avoid over-parameterization and the loss of degrees of freedom. The selection results reveal a highly consistent pattern across the 34 provinces, with all variables entering the model at lag order one, indicating a relatively homogeneous dynamic structure across cross-sectional units.

Table 6. ARDL Individual Lag Selection of Both Model

Province	GRDP/Capita	Flood	FDI	DDI
Average of Sumatera Island	1	1	1	1
Average of Jawa Island	1	1	1	1
Average of Bali, NTT, and NTB	1	1	1	1
Average of Sulawesi Island	1	1	1	1
Average of Maluku and Papua Island	1	1	1	1
Panel-ARDL	1	1	1	1

Based on this evidence, the optimal panel lag specification is defined as ARDL (1, 1, 1, 1), implying that both the dependent variable and all regressors are included with one lag. This specification is consistently applied to both empirical models. The first model examines the impact of flood disasters on GRDP per capita, incorporating foreign direct investment (FDI), government spending, and the Human Development Index (HDI) as explanatory variables. The second model analyzes the effect of flood disasters on income inequality, with economic growth and population growth included as additional regressors. Both models are estimated using panel data for 34 provinces in Indonesia over the period 2014–2024.

This lag structure captures short-run persistence and allows for distributed lag effects of the explanatory variables. The use of a uniform lag specification maintains model parsimony while ensuring a consistent representation of the underlying dynamic relationships.

Following the specification of the lag structure, the estimation strategy for the panel ARDL model is defined using two alternative approaches: the Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) estimators, both of which allow for the joint estimation of short-run dynamics and long-run relationships (Tables 7 & 8). The Mean Group (MG) estimator is excluded due to the limited time dimension of the dataset, which is insufficient to produce reliable group-specific long-run estimates. Consequently, the analysis focuses on a comparison between the PMG and DFE estimators.

The selection between these estimators is formally evaluated using the Hausman test for both models. The results yield a p-value of 0.000, which is below the 0.05 significance level, leading to the rejection of the null hypothesis. This finding consistently supports the preference for the Dynamic Fixed Effects (DFE) estimator over the Pooled Mean Group (PMG) estimator.

The DFE approach assumes homogeneity in long-run coefficients across cross-sectional units while allowing short-run dynamics and intercepts to vary. This specification is well suited to inter-provincial analysis in Indonesia, where provinces are likely to share common long-term structural relationships due to national policies and an integrated economic system, yet exhibit heterogeneous short-run adjustment processes driven by differences in regional capacity, institutional quality, and exposure to local shocks, including natural disasters.

Table 7. Hausman Test Result for the Flood Impact Model on GRDP per Capita

	Coeff.		Difference	Std. Error
	DFE	PMG		
log_floodnum L1.	-0.476976	0.0323017	-0.0799994	0.0181238
log_FDI L1.	0.0654784	0.3865945	-0.3211161	
log_govspend L1.	-0.6987782	-0.5160396	-0.1827386	
log_HDI L1.	10.13847	1.114842	9.02363	0.7047406
Prob > Chi2	0.0000***			

Table 8. Hausman Test Result for the Flood Impact Model on Inequality

	Coeff.		Difference	Std. Error
	DFE	PMG		
Flood_Numb L1.	-0.0002011	0.0018477	-0.0020489	0.0000721
Pop_Growth L1.	0.0094901	0.0961098	-0.0866197	0.0043678
Ec_Growth L1.	-0.0000446	0.0130105	-0.0130552	0.0005468
Chi2	1340.33			
Prob > Chi2	0.0000***			

Based on the PARDL-DFE estimation results, the short-run analysis shows that the number of flood events has a negative and statistically significant effect on per capita GRDP (coefficient = –0.0135; $p < 0.05$). This indicates a 1% increase in flood frequency decreases provincial per capita GRDP by approximately 0.013% in the short term. These findings also suggest that floods may cause immidiate losses in economic activities due to disruption in production and damaged infrastructures. This result is consistent with (Shaari et al., 2019), who demonstrated that flood frequency negatively affected short-term GRDP growth in Malaysia. Furthermore, Shaari et al. (2016) suggest that floods had lowered mining sector GRDP growth. According to their study, the frequency and duration of flood events significantly influence the extent of economic contraction, as production activities are constrained in the immediate aftermath of flooding.

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An important component of PARDL is the Error Correction Model (ECM) coefficient, which is –0.4001 and is statistically significant at the 5% level. This value represents that approximately 40% of short-run deviations from the long-run equilibrium are corrected in each period, suggesting that the regional economic system has a moderate ability to adjust and return to equilibrium following a flood-induced shock.

In contrast, other explanatory variables such as FDI, government expenditure, and HDI do not exhibit significant short-run effects on per capita GRDP in the short run. This implies that these factors neither contribute to nor mitigate the short-term fluctuations in per capita GRDP. It is plausible that their influence operates over a longer time frame. For instance, in developing countries, FDI may initially exert a negative impact on economic growth before yielding positive outcomes in the long run, as the benefits of investment often take time to materialize through mechanisms such as technology transfer, human capital accumulation, and productivity enhancement (Gupta & Garg, 2015). Similarly, government spending may also be a long-term endeavor that gives benefit per capita GRDP after a longer period.

Table 9. PARDL-DFE Estimation Results: Short-Run Impact of Flooding on GRDP per Capita

GRDP_Cap	Coeff.	Std.Error	Z	P > |Z|	[95% conf. interval]	
Short-Run						
ECM	-0.400103	0.047551	-8.41	0.000***	-0.493301	-0.306905
log_floodnumb D1.	-0.013544	0.0068554	-1.98	0.048***	-0.02698	-0.000108
log_FDI D1.	0.0044462	0.0066073	0.67	0.501	-0.008503	0.017396
log_govspend D1.	-0.001097	0.0554653	-0.02	0.984	-0.109807	0.107612
log_HDI D1.	0.1563528	0.4672524	0.33	0.738	-0.759445	1.072151
Cons	-4.695211	1.186825	-3.96	0.000***	-7.021345	-2.369077

Beyond the short-term, flooding has also been shown to have a persistent long-term effect on economic performance. The findings of this study support evidence that floods decrease economic performance in the long run. Based on the PARDL-DFE model (Table 7), the flood coefficient (log_floodnumb) is negative and statistically significant (–0.4769; $p < 0.05$), indicating that a 1% increase in the number of flood events is associated to approximately 0.48% decline in per capita GRDP. In other words, flooding does not just damage infastructure and business in short run but also weaken the economic performance over time.

This result aligns with the findings by Parida & Prasad Dash (2020), who found that floods, particularly through increased economic losses, affected populations, and damaged areas, sigificantly decrease per capita GRDP growth in India. Raddatz (2009) also revealed that when compared to geological disaster, climate-induced disasters tend to have more profound economic consequences in the long term. This difference may arise due to the reccurent nature of flooding, which further generates accumulative loss and impact through disrupted economic production activity, damage to human capital, and reduced economic resilience. As suggested by Noy & Nualsri (2007b), the decline in per capita GRDP after flooding may indicate the increased loss in human capital, thereby disrupting the foundation of economic activities.

In contrast to the adverse impact of flooding, foreign direct investment (log_FDI) has a positive and significant effect on per capita GRDP (coefficient = 0.0655; $p < 0.01$). This indicates that a 1% increase in FDI contributes to a 0.07% rise in per capita GRDP. This finding contrasts with the short-term results, which showed that FDI had no significant effect. This may be due to the notion that the benefits of foreign investment generally take longer periods to generate impact. In the Indonesian context, foreign investment is usually directed toward infrastructure development, industrial expansion, and technology transfer, whose economic impacts tend to unfold gradually. Over time, improvements in productivity and the spillover effects generated by foreign investment are likely to foster sustained economic growth.

Meanwhile, government expenditure (log_govspend) exhibits a negative and significant coefficient (–0.6988; $p < 0.01$), indicating that a 1% increase in government spending is associated with a 0.70% reduction in per capita GRDP in the long run. Lakat et al., (2025) argue that this may be due to the delayed return of investment, inefficiencies in resource allocation, or higher proportion of spending on comsumtive expenditures.

Conversely, the Human Development Index (log_HDI) exerts a positive and highly significant influence on per capita GRDP (coefficient = 10.138; $p < 0.01$), imply that a 1% improvement in HDI increases per capita GRDP by approximately 10.14%. This finding is aligned with previous studies demonstrating that HDI has positive impact on GDP per capita in ASEAN member countries (Elistia & Syahzuni, 2018). This finding highlights the pivotal role of human capital development, through advancements in education, health, and living standards, in fostering sustained regional economic growth.

Overall, the results confirm that flood risk management policies are essential to minimize the adverse impacts of floods on the growth of real per capita GRDP (Parida et al., 2021). Strengthening flood mitigation, improving resilience as well as adaptive capacity are crucial to ensure the sustainability of economic growth and welfare. Additionally, increase in per capita GRDP can also be driven by higher levels of foreign direct investment and improvements in the components of the Human Development Index, both contribute to long-term economic growth.

Table 10. PARDL-DFE Estimation Results: Long-Run Impact of Flooding on GRDP per Capita

GRDP_Cap	Coeff.	Std.Error	Z	P > |Z|	[95% conf. interval]	
Long-Run						
log_floodnumb L1.	-0.476976	0.0229109	-2.08	0.037***	-0.092602	-0.002793
log_FDI L1.	0.065478	0.0199896	3.28	0.001***	0.026299	0.104657
log_govspend L1.	-0.698778	0.1566868	-4.46	0.000***	-1.005879	-0.391677
log_HDI L1.	10.13847	1.101075	9.21	0.000***	7.98040	12.29654

Disasters generally have a disproportionate impact on vulnerable groups, as these populations often lack sufficient resources and financial capacity to cope with and recover from such events. Consequently, the adverse effects of disasters are typically more severe among disadvantaged groups. Moreover, disasters can exacerbate income inequality between richer and poorer households (Silva Araújo et al., 2022; Tovar Reaños, 2021), as wealthier groups typically have better access to resources that enhance their resilience and recovery. Over time, these differences in adaptive capacity may further intensify pre-existing socioeconomic inequalities, potentially increase to more structured disparities.

In the short term (Table 8), the estimation result reveals an interesting dynamic. The Error Correction Mechanism (ECM) coefficient is negative and statistically significant at the 5% level, with a value of –0.506. This result implies that approximately 50.6% of short-term disequilibria are corrected toward long-term equilibrium each year. In other words, reflecting a moderate speed of adjustment in the regional economic system following shocks induced by floods. This finding also confirms the existence of a short-term relationship between flooding and income inequality.

However, floods appear to slightly reduce income inequality, with an estimated coefficient of –0.000083, significant at the 5% level. This result suggests that each additional flood event is associated with the reduction of 0.000083 points in the Gini ratio. However, it does not mean that higher risk of floods will lead to improvement in welfare. Rather, this phenomenon may occur because floods temporarily depress income across all socioeconomic groups, thereby narrowing income disparities in the short term.

In addition, it is also possible that people with higher income experience higher losses, therefore may contribute to lowering the inequality. This result is in contrast with hypothesis that disaster will exacerbate the existing inequality. Brata (2022) using Indonesian provincial-level data, indeed found that disasters rising income inequality eventhough only two years following a disaster. Meanwhile, the estimation results indicate that other explanatory variables, population growth and economic growth, do not have statistically significant effects on inequality in the short term. This finding contrasts with previous studies suggesting that economic growth can exacerbate inequality, as the benefits of economic growth tend to be captured more by higher-income groups (Rubin & Segal, 2015). Similarly, the insignificant impact of population growth implies that population increases do not immidiately influence income distribution in the short term.

Table 11. PARDL-DFE Estimation Results: Short-Term Impact of Flooding on Inequality

Inequality	Coeff.	Std.Error	Z	P > |Z|	[95% conf. interval]	
Short-Run						
ECM	-0.506436	0.0468872	-10.80	0.000***	-0.598333	0.414539
Flood_Numb D1.	-0.000083	0.000033	-2.50	0.013***	-0.00015	-0.000017
Pop_Growth D1.	-0.000264	0.0022348	-0.12	0.906	-0.004644	0.004116
Ec_Growth D1.	0.0000518	0.0002179	0.24	0.812	-0.000375	0.000479
Cons	0.172325	0.0168124	10.25	0.000***	0.139427	0.205324

In the long run (Table 9), flood disasters exert a negative and statistically significant impact on income inequality in Indonesia. Specifically, each additional flood event is associated with a 0.000201-point reduction in the Gini ratio. This implies that regions experiencing more frequent floods tend to exhibit lower levels of income inequality over time. This finding aligns with the study by Eskander & Fankhauser (2022) in Pakistan, which reported that floods can lead to a reduction in income inequality because they disrupt agricultural activities and decrease income levels across different social groups. These results also aligned with the result in short-term impact. Although the result is ambigous, it may occur because floods may damage more productive assets of wealthier groups, resulting in the decline of their income. On the other hand, the lower income groups may do not possess as many as productive assests as the wealthier, experience smaller losses. As a result, the income gap between the two groups becomes narrow. This interpretation, however, needs further investigation to clarify the transmission mechanisms through which an increase in flood frequency may reduce inequality.

Table 12. PARDL-DFE Estimation Results: Long-Term Impact of Flooding on Inequality

Inequality	Coeff.	Std.Error	Z	P > |Z|	[95% conf. interval]	
Long-Run						
Flood_Numb L.1	-0.000201	0.0000753	-2.67	0.008***	-0.000349	-0.000053
Pop_Growth L1.	0.0094901	0.0044154	2.15	0.032***	0.0008361	0.018144
Ec_Growth L1.	-0.00005	0.000551	-0.08	0.935	-0.001126	0.001036

In contrast, population growth exhibits a positive and significant relationship with income inequality, where a 1% increase in population growth is associated with a 0.009-point rise in inequality. This result is contrast to previous study by Butler et al. (2020) who found that population growth leads to reduction in income inequality in rural America. The reason behind the relationship may be due to higher youth dependency ratio (Odusola et al., 2017). The result of this study suggests that the population growth without sufficient job creation may intensify disparities between different income groups. Meanwhile, economic growth shows a negative but statistically insignificant association with inequality, indicating that the expansion of economic output has not yet translated into a more equitable income distribution at the provincial level. This is possibly due to imbalance benefits across different provinces.

3.2 DISCUSSION

This empirical study shows that environmental shocks, particularly floods, can impact the economic landscape in Indonesia. In both the short and long term, flooding events have been shown to reduce per capita GRDP. However, this study is unable to explain the mechanism on how flooding reduces per capita GRDP. The flooding pattern in Indonesia is mostly recurrent, driven by tidal surge, river overflows, or urban drainage failure. Based on flood data, there has been an upward trend in flood frequency in Indonesia over the past ten years. Furhtermore, the Intergovernmental Panel on Climate Change (IPCC), (2023) project that climate change will continue to exacerbate the frequency and intensity of flooding events due to changes in rainfall patterns. This pattern can lead to a reduction in per capita GRDP due to disruptions to daily commercial activities, damage to transportation networks, and crop failures, which in turn hinder productivity. For example, coastal communities in Semarang City experience flooding 1-7 times per month during the rainy season, leading to a decline in community welfare, partly due to loss of income and employment (Purnomo et al., 2023). The loss of people's livelihoods can affect aggregate productivity.

Conversely, in both the short and long term, flooding has been shown to reduce inequality, as reflected in the Gini ratio. Empirically, post-disaster inequality reduction typically occurs through increased social assistance and public transfers. In the German case, government incentives and additional fiscal policies after floods directed to low-income households have impact on income redistribution (Tovar Reaños, 2021). T the interpretation that floods may mitigate inequality necessitates a cautious approach due to potential measurement biases, specifically regarding the application of the Gini index. Research by Vin & Kawasaki (2024) utilized "total net cash" as a primary metric rather than a standard income index, arguing that income often fails to accurately represent economic stability during extreme events. This reduction in inequality does not seem to translate into an increase in the welfare of disadvantaged groups; rather, it may result in a decrease in income for wealthy groups. Floods also typically damage higher-productive assets, often owned by wealthy groups, resulting in more significant income losses. This phenomenon aligns with the findings of Eskander & Fankhauser (2022), that disasters can temporarily reduce the income gap in Pakistan. However, Eskander & Fankhauser (2022) stated that this relationship is ambiguous. Furthermore, in their study, the decrease in inequality occurred due to decreased diversification in the source of income. In fact, other studies have shown that disasters, including floods, have a negative impact on income distribution, as demonstrated oleh Bista (2020) using household data in Nepal following floods and landslides. Similarly, in the German context (Tovar Reaños, 2021), flood damage was shown to increase inequality. In that study, post-flood welfare increased inequality by 0.14%, with the greatest losses being felt by low-income households. Therefore, the findings in this study suggest that floods may damage the capital of higher-income groups, thereby reducing the income of the wealthy.

Despite the apparent reduction in inequality due to flooding, the structural reality is quite the opposite. Referring to the research conducted by Bangalore et al. (2017), disasters disproportionately impact vulnerable groups due to overexposure to hazards, high vulnerability, reduced ability to cope and recover, and impacts on education and health. These vulnerability characteristics and how they influence the severity of disaster economic impacts need further examination in a subnational context to gain a comprehensive picture.

On the other hand, this study also found that in the short and long term, explanatory variables such as FDI, government expenditure, and HDI did not significantly influence the province's per capita GRDP. However, in the long term, FDI and HDI had a positive effect on per capita GRDP. This confirms that FDI only has a positive and significant impact on per capita GRDP over the longer term. Unfortunately, government expenditure did not have a negative impact on per capita GRDP in the long term. This may indicate an efficiency gap in public spending allocation. Thus, government spending may not necessarily have an optimal impact on per capita GRDP.

Furthermore, the research findings provide important perspectives on the role of population growth and economic growth on inequality in the short and long term. In the short term, population growth and economic growth do not have a significant impact on inequality. However, in the long term, population growth is positively correlated with an increase in the Gini ratio, or in other words, increasing inequality. In other words, population growth is not accompanied by increased welfare and job creation tends to widen inequality in the future. This finding aligns with the research of Odusola et al. (2017), which found that rapid population growth can exacerbate inequality due to inadequate labor wages

4. CONCLUSION

This research analyzes the short and long-run effect of flood occurrence on the regional economic performance and inequality in Indonesia using PARDL based on data during 2014-2024 at provincial level. Two models are developed to understand the impact of flood on DRDP per capita and gini ratio. This research found that flood singificantly reduce GRDP per capita both in short and long run periods. In longer time, a 1 percent increase in flood occurrence could potentially decrease GRDP per capita by 0.48 percent. The results also show that flood occurrence could lower the gini ratio both in short and long-run. This finding is interesting because each flood event reduces income inequality by 0.0002 points in the long run. This finding suggests that the impact of flooding tends to narrow income inequality, possibly because economic losses are felt equally across all groups, or because post-disaster government interventions are relatively more targeted at lower-income groups.

Theh limitation of this study lies in the use of inequality indicators such as the Gini ratio, which may introduce measurement bias. The assertion that the Gini ratio captures relative income distribution while failing to fully reflect absolute welfare changes across demographic groups is a critical methodological consideration. Consequently, future research should complement the Gini ratio with alternative metrics to provide a more comprehensive result. Furthermore, this study also has weaknesses in explaining the mechanisms by which flooding can impact the economy.

Overall, the results of this study confirm that flood disasters in Indonesia negatively impact regional economic growth in the long term. Therefore, there is a need to integrate flood risk reduction initiatives into regional economic development. For example, by increasing regional economic resilience, economic infrastructure resilience, improving human resource development, and public spending efficiency to minimize the long-term economic impact of flood disasters. Furthermore, the research findings need to be further explored, including the mechanisms by which floods reduce per capita GRDP and explore how floods can reduce inequality.

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