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# Exploring the Regional Multidimensional Poverty Pattern in Indonesia: Does Climate Matter?

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**Abstract**

**Research Originality:** This study develops a comprehensive regional measure of poverty using the capability approach to understand the pattern of multidimensional poverty in Indonesia.

**Research Objectives:** This study has two objectives: first, to construct and examine multidimensional poverty levels in 33 Indonesian provinces from 2010 to 2020; and second, to investigate the association between climate variables and the Multidimensional Poverty Index (MPI).

**Research Methods:** The MPI is measured through equal weighting of 20 indicators. A pooled ordinary least squares regression was used to study the relationship between the climate variables and MPI.

**Empirical Results:** The findings indicate that most provinces have experienced a decrease in poverty over the past decade. However, significant inequality persists among provinces, particularly in the eastern regions of Indonesia. Further analysis reveals that temperatures exceeding 25.25 °C may lead to an increase in the MPI, while precipitation exceeding 9.5 mm/day is associated with a decrease in the MPI.

**Implications:** This study underscores the importance of incorporating climate change concerns, specifically increasing temperatures and unpredictable precipitation, into poverty reduction strategies and highlights the need for region-specific policies to address the multifaceted nature of poverty in Indonesia effectively.

**Keywords:**

multidimensional poverty index; temperature; precipitation; capability approach; pooled OLS regression

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## INTRODUCTION

The topic of the interrelation between poverty and climate change has received increased attention in academic research and has been a fascinating topic to discuss. Existing empirical evidence indicates a vicious cycle between climate change and poverty, in which poverty exacerbates the suffering of disadvantaged groups due to climate change. Research regarding the linkage between climate change and poverty has been continuously conducted by focusing on two main aspects: the economic impact of climate change at the household level (Li et al., 2024; Schleypen et al., 2024; Etwire, 2024; Yagaso et al., 2024; Otrachshenko et al., 2024; Amare & Balana, 2023), and at the aggregate level (Gill et al., 2024; Demirhan & Bayraktar, 2025; Roy, 2024; Yuan et al., 2024; Huynh & Hoang, 2024). For instance, Sinha et al. (2022) confirm the positive link between poverty and vulnerability to climate change, whereby regions with high levels of poverty are also highly vulnerable to climate change, and vice versa. Sebukeera et al. (2023) suggest that climate variability has a significant impact on the likelihood of a household falling into poverty in Uganda.

On the other hand, a study by Mahjoubi and Mkaddem (2024), which utilized national-level data and spatial model analysis, suggests that climate change, precipitation, and temperature have both direct and indirect effects on poverty. Dang et al. (2023) identify the impact of high temperatures on poverty and inequality using subnational data analysis. Their findings suggest that both hotter and colder temperatures are associated with higher poverty rates and inequality.

Ogbeide-Osaretin et al. (2022) conducted a study using secondary data from 1980 to 2020 to explore the relationship between climate change, poverty, and inequality in Nigeria. The study concludes that there is a U-shaped relationship between temperature and inequality. Specifically, temperature has a significant negative impact on the Gini ratio, while the square of temperature has a positive effect on the Gini ratio. These findings indicate that as temperatures rise due to climate change, income inequality initially decreases because the effects are felt similarly across all income levels. However, as temperatures continue to rise, the poor become increasingly exposed and unable to afford measures to mitigate the impact, which affects their income sources and widens the income inequality gap.

Barbier and Horchard (2017) investigated whether the spatial distribution of rural populations in 2000 affected changes in poverty rates from 2000 to 2012 in 83 developing countries. The study found no direct evidence that climate change itself changes poverty levels. However, climate change indirectly affects poverty by altering the effectiveness of economic growth in reducing poverty. Therefore, while promoting economic growth is often the most effective means, it is not sufficient on its own to address the challenges faced by large rural populations living in less favorable and remote agricultural areas vulnerable to climate change. Meanwhile, Islam and Winkel (2017) suggest that reducing inequality could help contain the adverse effects of climate change and mitigate climate change itself, while Markkanen and Anger-Kraavi (2019) underline that well-designed


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and carefully implemented climate change mitigation policies could potentially provide opportunities to address gender, health, and economic inequalities.

To estimate the relationship between climate change and poverty, most researchers have developed poverty measurements using monetary indicators such as assets and income as proxies for poverty. Meanwhile, non-monetary metrics of poverty have received little attention in the climate change literature. Estimates relying only on monetary indicators can be misleading (Hallegatte et al., 2020) and may fail to reflect the distributional impacts of climate change on poverty. Under these circumstances, this approach may disproportionately obscure the impacts on specific regions and hinder the development of effective mitigation policies by governments (Hallegatte et al., 2018).

It is undeniable that there is no superior approach to measuring poverty and inequality compared to others to date. The Gini coefficient is a very popular and commonly used measure to gauge inequality. However, some other methods are also commonly used to measure inequality, such as the Theil Index and the Coefficient of Variation (Allison, 1978), as well as the Williamson coefficient (Williamson, 1965). So far, the distribution of income has been widely used as an indicator for identifying inequality. However, measuring inequality should not only consider one aspect, because it may also be linked to many aspects of an individual's life (Quadrado et al., 2001). Inequality should encompass all socio-economic aspects of livelihood and well-being, including health, education, technology, communication, and infrastructure (Alkire & Foster, 2011). Adopting a single indicator, such as the Gross Domestic Product (GDP) per capita, may also lead to an ambiguous interpretation, as the same indicator is often used to study a country's economic growth or development. It is believed that relying solely on economic performance indicators is insufficient to calculate development or well-being accurately. As stated by Sen (1980), although it may be valuable to identify inequality based on income data, the income indicator cannot fully capture an individual's well-being due to its simplicity. Therefore, numerous multidimensional indices have recently been developed, acknowledging the value of pondering multiple aspects of life.

Generally, GDP has been the most widely used indicator of regional inequality in Indonesia. Although many studies have aimed to develop new indices that capture the socio-economic dimensions of inequality, there is a limited body of research and empirical evidence specific to Indonesia. Most previous studies (Akita & Miyata, 2018; Tadjoeddin et al., 2016; Tadjoeddin & Chowdhury, 2019) have relied on GDP to understand inequalities between regions, provinces, and even districts in Indonesia. However, as previously mentioned, GDP per capita provides an ambiguous result and is insufficient for measuring development across multiple aspects of human well-being. Therefore, it is crucial to develop and explore alternative indices and measurements that take into account the multidimensional aspects of human development, in order to gain a more comprehensive and "realistic" understanding of regional disparities in Indonesia over time.

This study aims to achieve the following two objectives: better to understand poverty and its interrelationship with climate change. First, it constructs and examines the level of multidimensional poverty in 33 provinces in Indonesia from 2010 to 2020. Second, it examines the relationship between climate change and multidimensional poverty in Indonesia. This research remains highly relevant and interesting to discuss because climate change and poverty are two of the most pressing global challenges of our time, specifically in the context of developing countries, such as Indonesia, with complex and evolving interactions. Both remain important global agendas as Sustainable Development Goals (SDGs), specifically SDGs #1 and 13. As previously explained, numerous studies have investigated the relationship between climate change and poverty. However, most have relied heavily on income and assets to measure poverty. This study, in contrast, examines critical non-monetary dimensions, including health, education, economics, and housing. What sets this study apart is its comprehensive integration of both monetary and non-monetary metrics to assess poverty, providing a more holistic view of how climate change exacerbates poverty in a broader sense. The novelty of this research lies in its innovative framework, which links climate variables to MPI, offering policymakers a more nuanced understanding of the distributional effects of climate change on poverty. By doing so, this study not only fills a significant gap in the literature but also provides actionable insights for designing targeted and equitable climate mitigation and adaptation policies.

This study makes a significant contribution to the existing literature in four key ways. First, it addresses a gap by proposing an alternative approach to examining regional multidimensional poverty, moving beyond GDP per capita through the capability approach outlined by Sen (1980). Second, the study explores the link between poverty and climate change. Given that Indonesia ranks among the top three countries in terms of natural hazard risk, this research could provide insights into how to reduce poverty while mitigating the risks associated with climate change. Third, the case study focuses on Indonesia, an archipelagic and heterogeneous country, making it particularly relevant for policymaking, as it takes into account regional characteristics, such as demographics and geographic conditions. Finally, the study utilizes large, recent, nationally representative secondary data to analyze multidimensional poverty in the country.

## METHODS

In order to examine multidimensional poverty in Indonesia, this study identifies four domains of human capabilities. The data collected from the National Bureau of Statistics of Indonesia (BPS) encompassed 33 provinces. Due to some indicators having missing values in certain years, only data from 2010 to 2020 were used. Meanwhile, the historical climate data from 2010 to 2020 collected based on the weather station in each province in Indonesia were aggregated at the provincial level. Overall, 186 stations were distributed around the Indonesian region, and the geographic location of each station (latitude and longitude) is used to identify the weather from the NASA POWER source. Considering that one province may have more than two stations, the climate was then aggregated by using an area-weighted average, as shown in the following formula.


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$$X_{i,t}^{temp} = \frac{\sum_{s=1}^{N} temp_{i,s} \,.\, a_{i,s}}{\sum_{s=1}^{N} a_{i,s}}$$

and

$$X_{i,t}^{prec} = \frac{\sum_{s=1}^{N} prec_{i,s} \,.\, a_{i,s}}{\sum_{s=1}^{N} a_{i,s}} \quad (1)$$

where $X_{i,t}^{temp}$ and $X_{i,t}^{prec}$ are the temperature and precipitation area-weighted average temperature in province $i$ at year $t$, $temp_{i,s}$ the temperature of a particular meteorological station $s$ in province $i$, $N$ is the number of stations over the province $i$, $a_{i,s}$ is the area of Thiessen polygon of station s in province $i$. The area ($m^2$) of Thiessen polygon in each station is measured using QGIS software.

As previously explained, the data used for measuring multidimensional poverty in Indonesia were obtained from the National Bureau of Statistics of Indonesia, covering 33 provinces over the period 2010–2020. Since the data contains variables with different formats or units and cannot be aggregated directly, the min-max normalization method is then implemented. The formula is presented in Equation (2) and Equation (3). In detail, Equation (2) is applied when the indicator used to construct the MPI has a positive impact. Meanwhile, Equation (3) is calculated when the indicator negatively affects the level of multidimensional poverty. Equations (2) and (3) are as follows:

$$x_{ijt} = \frac{k_{ijt} - x_{jmax}}{x_{jmax} - x_{jmin}} \quad (2)$$

$$x_{ijt} = \frac{x_{jmax} - k_{ijt}}{x_{jmax} - x_{jmin}} \quad (3)$$

Where,

$x_{ijt}$ is the normalized value of the $j^{th}$ indicator in $i$ province on year $t$,
$k_{ijt}$ is the actual value of the $j$-th indicator in $i$ province on year $t$,
$x_{jmax}$ is the maximum value of the $j$-th indicator.

For the purpose of measuring the MPI of each province, this study employs an equal-weight approach to calculate the composite index of each dimension. This approach has been applied in constructing the household's MPI and various studies. Considering that each dimension and indicator used in this study are equally crucial, four dimensions are given equal weight (1/4 = 0.25 of each dimension). Each indicator within its dimension is also given equal weight. It is worth noting that some indicators may have some missing data for some years. In this case, this study follows the assumption that there may not be a sudden change from one year to the following one, so it can be undertaken by counting the previously available year (Parente, 2019). Table 1 shows the list of MPI dimensions and their weights.

The calculation of the MPI is then aggregated by using additive aggregation through the following formula:

$$MPI_{it} = \sum_{j=1}^{m} w_j x_{ijt} \tag{4}$$

Where,

$MPI_{jt}$ is the multidimensional poverty index of $i$ province on year $t$,

$w_j$ is the weight of the $j$-th indicator,

$x_{ijt}$ is the normalized value of the $j$-th indicator in $i$ province on year $t$.

To understand how climate change affects multidimensional poverty in Indonesia, a pooled ordinary least squares regression is conducted to investigate the impact. The model is as follows:

$$MPI_{it} = \beta_0 + \beta_1 TEMP_{it} + \beta_2 PREC_{it} + \beta_3 Region_{it} + \beta_4 Lat_{it} + \beta_5 Long_{it} + \beta_6 Lat_{it} * Long_{it} + \varepsilon_{it} \tag{5}$$

where $MPI_{it}$ refers to the multidimensional poverty index of province $i$ in year $t$, $TEMP_{it}$ and $PREC_{it}$ are the independent variables of climate change, which indicate the temperature and precipitation in province $i$ at year $t$. $Region_{it}$ serves as a control variable representing the regions of west, central, and east. $Lat_{it}$ and $Long_{it}$ are the latitude and longitude of province $i$ in year $t$. The addition of $Region_{it}$, $Lat_{it}$ and $Long_{it}$ are to control the regional heterogeneity. $\beta_{1\text{-}6}$'s are the regression coefficients and $\varepsilon_{it}$ is the error term. Furthermore, Equation (6) is used to estimate the non-linear effect of temperature and precipitation. Previous studies (Burke et al., 2015; Henseler and Schumacher, 2019) found that the effect of temperature on economic growth is non-linear. The model is as follows:

$$MPI_{it} = \beta_0 + \beta_1 TEMP_{it} + \beta_2 TEMP_{it}^2 + \beta_3 PREC_{it} + \beta_4 PREC_{it}^2 + \beta_5 Region_{it} + \beta_6 Lat_{it} + \beta_7 Long_{it} + \beta_8 Lat_{it} * Long_{it} + \varepsilon_{it} \tag{6}$$

**Table 1. Dimension and Weights of MPI**

| Dimensions of Capabilities (weights) | Indicators (weights) | Unit of Measurement |
|---|---|---|
| Life and health (1/4) | Life expectancy rate (1/24) | Life expectancy at birth in year |
| | Malaria incidence (1/24) | Malaria incidence per 1000 people |
| | Prevalence of crime (1/24) | Risk of citizens become crime victims per 100000 people |
| | Completion of crime rate (1/24) | Percentage completion crime |
| | Death from natural disasters (1/24) | Number of deaths due to natural disasters |
| Education and learning (1/4) | Literacy rate (1/20) | Percentage of literate people aged 15 years and over |
| | School participation rate (1/20) | School participation rate (7-12 years) (in percentage) |
| | | School participation rate (13-15 years) (in percentage) |
| | Internet used rate (1/20) | Percentage of households ever accessing the internet in the last 3 months |
| | Ownership of computer (1/20) | Percentage of households owns computer |
| | Phone ownership (1/20) | Percentage of households owns fixed line telephone |


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| Dimensions of Capabilities (weights) | Indicators (weights) | Unit of Measurement |
|---|---|---|
| Economic (1/4) | Per capita income (1/20) | Regional Gross Domestic Products (RGDP) by expenditure |
| | Unemployment rate (1/20) | Unemployment rate (in percentage) |
| | Gini ratio (1/20) | Gini ratio |
| | Poverty rate (1/20) | Percentage of poor population |
| | Foreign Direct Investment (FDI) (1/20) | FDI realization (in million US$) |
| Housing (1/4) | Dwelling ownership status of own (1/16) | Percentage of households owns dwellings |
| | Improved sanitation (1/16) | Percentage of households who have access to improved sanitation |
| | Improved drinking water (1/16) | Percentage of households who have access to improved drinking water |
| | Access to electricity (source of lighting) (1/16) | Percentage of households with lighting source of state electricity |

## RESULT AND DISCUSSION

The descriptive statistics of the Multidimensional Poverty Index (MPI) scores for 33 provinces in Indonesia from 2010 to 2020 are presented in Table 2. The data show that, overall, Indonesia has experienced a reduction in multidimensional poverty over the past decade. The average MPI in 2010 was 0.513, with the maximum and minimum scores being 0.649 and 0.395, respectively. By 2020, the average MPI had gradually decreased to 0.368, with the maximum and minimum scores being 0.587 and 0.247, respectively.

**Table 2. Descriptive Statistics of MPI**

| Year | Mean | Min | Max. | Std. Deviation |
|---|---|---|---|---|
| 2010 | 0.513 | 0.395 | 0.649 | 0.054 |
| 2011 | 0.488 | 0.316 | 0.682 | 0.072 |
| 2012 | 0.464 | 0.294 | 0.657 | 0.070 |
| 2013 | 0.454 | 0.313 | 0.619 | 0.067 |
| 2014 | 0.445 | 0.278 | 0.609 | 0.070 |
| 2015 | 0.439 | 0.313 | 0.614 | 0.067 |
| 2016 | 0.421 | 0.272 | 0.673 | 0.070 |
| 2017 | 0.408 | 0.252 | 0.610 | 0.066 |
| 2018 | 0.396 | 0.255 | 0.581 | 0.061 |
| 2019 | 0.371 | 0.247 | 0.588 | 0.062 |
| 2020 | 0.368 | 0.247 | 0.587 | 0.060 |

Source: Authors' calculations

The trend of MPI for each province from 2010 to 2020 is illustrated in Figure 1 a-k. As shown in Figures 1a through k, all provinces in Indonesia have reduced their MPI. These results indicate that all dimensions and indicators used to construct the MPI—including life and health, education and learning, economic conditions, and housing—have improved from 2010 to 2020. Based on the estimates, the most significant dimension for reducing the MPI in Indonesia is life and health, particularly the indicators related to deaths from natural disasters and malaria incidence. Another highly contributing dimension is housing, specifically access to electricity and improved drinking water.

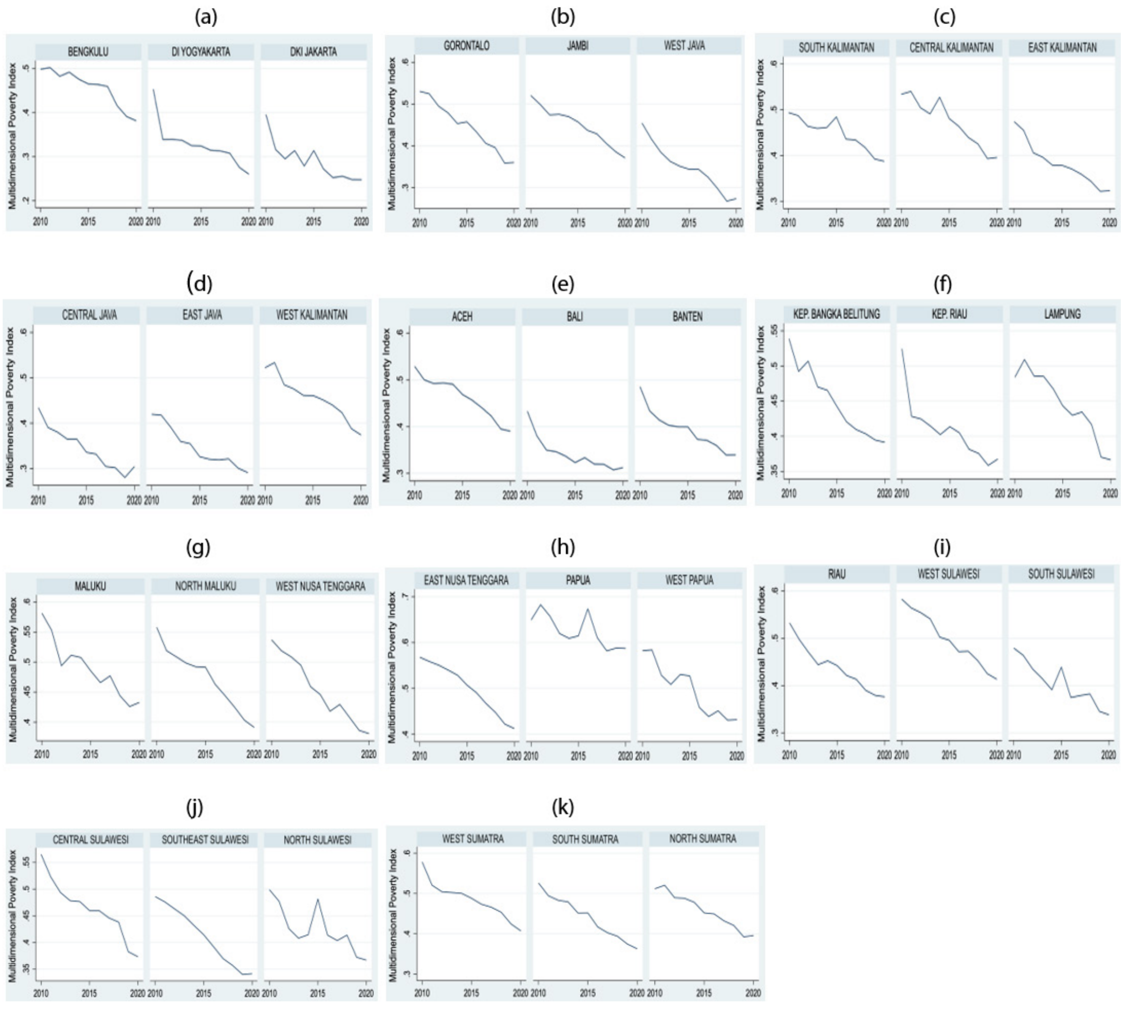
These findings align with previous studies. For example, Wink Junior et al. (2024) found that floods may increase the likelihood of people falling into poverty. Meanwhile, Yang et al. (2024) concluded that reducing malaria prevalence in households has a causal effect on increased wealth, and that increased wealth, in turn, contributes to further reductions in malaria prevalence. Similarly, Handayani et al. (2024) suggested that expanding access to stable electricity has a significant impact on poverty alleviation. Additionally, Ladi et al. (2021) found that water availability plays a critical role in shaping human development in Iran.

In 2010, around 14 provinces had MPI scores below 0.5, indicating lower levels of multidimensional poverty compared to the other 19 provinces. DKI Jakarta had the lowest MPI in 2010 (0.395), which decreased to 0.247 in 2020 (Figure 1). The observed reduction of approximately 37.48% in DKI Jakarta's MPI signifies a notable decline in multidimensional poverty (Figure 1a). This improvement can be attributed to several key factors, including enhanced access to healthcare, education, economic growth, and infrastructure development. Specifically, in the health and life dimension, DKI Jakarta has experienced an increase in life expectancy and a reduction in malaria incidence. According to Diwyarthi et al. (2023), improved accessibility to healthcare facilities is strongly associated with higher life expectancy and a better overall quality of life. In 2023, life expectancy in DKI Jakarta reached 73 years, the second highest among Indonesia's provinces (BPS, 2025). Moreover, since 2023, DKI Jakarta has been one of the five provinces in Indonesia to achieve malaria-free status (Jakarta Health Service, 2023).

As the economic powerhouse of Indonesia, DKI Jakarta has exhibited robust economic growth, with the economy expanding by 4.93% in the third quarter of 2024 compared to the same period in 2023 (BPS Jakarta, 2025). The city has also made significant investments in infrastructure development, including transportation networks, housing, and access to clean water, all of which are likely to have contributed to improvements in the overall quality of life. Novitasari et al. (2020) argue that infrastructure development—such as the expansion of roads, the establishment of additional hospitals, and improvements in waste management—has had a positive and significant impact on DKI Jakarta's GDP. Furthermore, improvements in sanitation and the expansion of junior high schools have likely contributed to enhanced living standards, as reflected in the region's rising Human Development Index.

A significant reduction in the MPI is also observed in other provinces, including DI Yogyakarta, West Java, and East Java (Figure 1a, b, and d). West Java, for instance, reduced its MPI from 0.455 in 2010 to 0.273 in 2020, representing a substantial decline of approximately 40% (Figure 1b). Similar to DKI Jakarta, this reduction suggests considerable improvements in key dimensions of poverty, particularly in the health and life dimension, as well as the economic dimension. This finding aligns with O'Donnell (2024), who argues that poor health is a significant contributor to poverty, with income loss due to illness or disability being a more significant factor in driving poverty. In the cases of DI Yogyakarta and East Java, both provinces achieved MPI scores below 0.3 by 2020 (Figure 1a), indicating a notable reduction in poverty levels. This can be primarily attributed to advancements in the health and life dimensions, as well as improvements in the housing dimension. These findings are consistent with Sunde (2024), who emphasized that poverty is predominantly driven by the lack of basic services, including limited access to healthcare and inadequate sanitation.

**Figure 1. The Pattern of The Multidimensional Poverty Index of Each Province in Indonesia During the Period of 2010-2020**




Furthermore, the notable improvements in the education and learning dimension have made a significant contribution to poverty reduction in DI Yogyakarta. In contrast, the rapid economic growth in East Java has been a crucial factor in fostering poverty reduction within the province. Spada et al. (2023) and Hofmarcher et al. (2021) highlight that increasing education can have a large impact on reducing poverty. Meanwhile, Balasubramanian et al. (2023) found that a 10% increase in GDP is associated with a reduction in multidimensional poverty of approximately 5%.

**Table 3. Linear and non-linear association of climate change with MPI**

| Variable | Linear effect | Non-linear effect |
|---|---|---|
| Temperature | -0.013*** (0.002) | -0.202*** (0.078) |
| Temperature$^2$ | | 0.004** (0.001) |
| Precipitation | 0.004** (0.001) | 0.019*** (0.007) |
| Precipitation$^2$ | | -0.001*** (0.005) |
| Region (Central) | 0.042*** (0.011) | 0.078*** (0.012) |
| Region (East) | 0.154*** (0.018) | 0.144*** (0.018) |
| Lat | -0.058*** (0.017) | -0.079*** (0.017) |
| Lat$^2$ | | -0.001** (0.000) |
| Long | -0.003*** (0.000) | -0.051*** (0.008) |
| Long$^2$ | | 0.000*** (0.000) |
| Lat x Long | 0.000*** (0.000) | 0.000*** (0.000) |
| Constant term | 1.129*** (0.110) | 6.840*** (1.013) |
| Number of Observation | 363 | 363 |
| R-Squared | 0.440 | 0.526 |
| F-Statistics | 39.90*** | 35.50*** |

Notes: Standard errors in parentheses. ***$p$-*value* < 0.01

Despite the overall reduction in MPI, a substantial gap has become apparent between the provinces. In 2015, three provinces in the eastern region of Indonesia—East Nusa Tenggara (NTT), West Papua, and Papua—still had high MPI scores above 0.5 (Figure 1h). Papua Province, in particular, did not show substantial improvement, continuing to experience high multidimensional poverty in 2018 and 2020. The possible explanation can be attributed to several factors, including a very high incidence of malaria and a high prevalence of crime. Additionally, Papua Province continues to have lower rates of literacy, lower school participation, lower regional income, poorer sanitation, and limited access to electricity.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In addition to these results, sensitivity and robustness tests were conducted to determine whether the MPI changes substantially if specific indicators are omitted and to verify the stability of the MPI. For this analysis, an alternative MPI was estimated using only four indicators: life expectancy at birth, school participation rate (7–12 years), school participation rate (13–15 years), and regional gross domestic product (RGDP). The results confirmed similar findings, as both the MPI and the alternative MPI used for the robustness test were found to be strongly correlated. The correlation coefficient of 0.849 indicates that the estimated MPI is robust.

The estimation results of climate change, represented by temperature and precipitation, on multidimensional poverty, using pooled ordinary least squares and Equation (5), are presented in Table 3. In general, all the independent variables are significant at a 1% significance level. The results indicate that higher temperatures are associated with a reduction in multidimensional poverty, as indicated by the negative coefficient of the temperature variable. On the other hand, an increased level of precipitation could positively contribute to the rising multidimensional poverty. In this case, a 1 mm/day increase in precipitation may be associated with a 0.004-point rise in MPI. In terms of region, the results reveal that provinces located in the East and Central regions of Indonesia tend to have higher MPI compared to provinces located in the West region.

Table 4 presents the estimation results regarding the non-linear relationship between climate change and multidimensional poverty. The results indicate a non-linear relationship between climate change and multidimensional poverty. Specifically, it is observed that temperature is associated with the MPI in a U-shaped manner, while precipitation impacts MPI in an inverted U-shaped manner. The findings suggest that at lower temperature levels, an increase in temperature results in a significant reduction in multidimensional poverty.

However, this effect changes after a specific threshold temperature is reached. Beyond this point, further increases in temperature lead to an increase in multidimensional poverty. The regression analysis identifies this turning point at approximately 25.25°C. The impact of higher temperatures above this turning point on multidimensional poverty can be attributed to several factors, including reduced agricultural productivity, exacerbated health conditions, decreased labor productivity, increased energy costs, water scarcity, and extreme events such as droughts. Several previous studies, such as Saeed et al. (2022), have revealed that increased heat stress due to high temperatures can reduce workers' productivity and, in turn, lead to higher poverty rates.

On the other hand, this study reveals that higher levels of precipitation contribute to an increase in multidimensional poverty up to an optimal level. Beyond this optimal level, further increases in precipitation result in a reduction in the MPI. The turning point for precipitation is identified as 9.5 mm/day. These results imply that while higher precipitation can exacerbate poverty up to 9.5 mm/day, beyond this threshold, increased precipitation may help reduce poverty. The impact of precipitation on multidimensional poverty may be related to the occurrence of extreme events, such as flooding and sea level rise, which are associated with high levels of precipitation. However, at specific points, increased precipitation improves water availability, which is essential for agriculture and drinking water supplies. Matsumoto et al. (2021) suggest that although regional GDP generally decreases due to climate change, some areas may experience an increase in GDP because of their comparative advantage.

Table 5 presents the estimation results for each indicator considered in the construction of the MPI, as shown in Table 1. In total, 19 indicators are used for the MPI calculation. However, the indicator of deaths from natural disasters is excluded from the estimation due to limited data availability. The results reveal several key findings.

First, the analysis indicates that temperature and precipitation exhibit distinct effects on the indicators of MPI, confirming the presence of a non-linear relationship with multidimensional poverty. Specifically, temperature generally demonstrates a U-shaped relationship with economic dimensions, including RGDP, unemployment rate, and FDI, as well as dwelling ownership. This pattern suggests that an initial increase in temperature reduces these indicators, but beyond a certain threshold, further increases result in improvements.

Conversely, temperature exhibits an inverted U-shaped relationship with life and health dimensions, including life expectancy rates and malaria incidence, as well as education dimensions (literacy rates, school participation rates, internet usage, computer ownership), the Gini ratio, improved sanitation, improved drinking water, and access to electricity. This result implies that an initial rise in temperature leads to increases in these indicators up to a certain point, after which further increases in temperature result in declines.

Third, while the effects of temperature are observed across all MPI indicators, the impact of precipitation is not uniformly distributed, particularly concerning its influence on the life and health dimension and the economic dimension. The analysis reveals that precipitation has an inverted U-shaped effect on the poverty rate, indicating that initial increases in precipitation improve these economic indicators until a certain optimal level is reached, beyond which further increases lead to deterioration. Meanwhile, precipitation shows a significant U-shaped relationship with most indicators in the education and learning dimension.

As a tropical country, Indonesia typically experiences an average minimum temperature of 22.8°C and a maximum of 30.2°C (World Bank, 2021). While the country may be able to adapt to temperature increases within this range, temperatures exceeding these typical levels can pose significant risks to human health, daily activities, and the environment. Prolonged heat beyond the usual range can exacerbate heat stress, which, in turn, affects labour productivity (Dasgupta et al., 2021; Liu et al., 2021) and public health, potentially leading to an increase in heat-related illnesses and even fatalities. Similarly, Roy (2024) suggests that an increase in the annual average temperature would lead to a decline in life expectancy at birth. Furthermore, the temperature rise will interact with the rainfall cycle, contributing to a further decline in life expectancy.


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**Table 5. Impact of Climate Change on MPI Indicators**

| Variable | Temperature | Temperature² | Precipitation | Precipitation² |
|---|---|---|---|---|
| **Life and Health** | | | | |
| Life expectancy rate | 0.817*** (0.188) | -0.016*** (0.003) | -0.022 (0.001) | 0.003** (0.001) |
| Malaria incidence | 0.345*** (0.115) | -0.007*** (0.002) | -0.010 (0.010) | 0.000 (0.000) |
| Prevalence of crime | -0.016 (0.230) | 0.000 (0.004) | -0.022 (0.021) | 0.002 (0.002) |
| Completion of crime | 0.123 (0.213) | -0.002 (0.004) | -0.009 (0.019) | 0.001 (0.001) |
| Education and Learning | | | | |
| Literacy rate | 1.360*** (0.129) | -0.026*** (0.002) | -0.003 (0.012) | -0.000 (0.000) |
| School participation rate (7-12 years) | 0.985*** (0.098) | -0.018*** (0.002) | -0.012 (0.009) | 0.000 (0.000) |
| School participation rate (13-15 years) | 1.342*** (0.192) | -0.025*** (0.004) | -0.055*** (0.017) | 0.003*** (0.001) |
| Internet used rate | 0.687** (0.342) | -0.012* (0.007) | -0.063** (0.031) | 0.005** (0.002) |
| Ownership of computer | 1.150*** (0.265) | -0.021*** (0.005) | -0.043* (0.042) | 0.003* (0.002) |
| Phone ownership | 0.171*** (0.182) | -0.003 (0.003) | -0.027 (0.016) | 0.003** (0.001) |
| Economic | | | | |
| Regional Growth Domestic Product | -0.409* (0.228) | 0.008* (0.004) | 0.028 (0.021) | -0.001 (0.001) |
| Unemployment rate | -0.587** (0.227) | 0.011** (0.004) | -0.043** (0.021) | 0.002*** (0.001) |
| Gini ratio | 0.029** (0.215) | -0.000** (0.004) | 0.017 (0.019) | -0.000 (0.001) |
| Poverty rate | 0.007 (0.177) | -0.000 (0.003) | 0.055*** (0.016) | -0.003*** (0.001) |
| FDI | -1.215*** (0.206) | 0.023*** (0.003) | 0.034* (0.019) | -0.002 (0.001) |
| Housing | | | | |
| Dwelling ownership | -1.272*** (0.242) | 0.025*** (0.005) | 0.033 (0.016) | -0.002* (0.002) |
| Improved sanitation | 0.552** (0.242) | -0.010** (0.005) | -0.087*** (0.022) | 0.005*** (0.001) |
| Improved drinking water | 0.611** (0.259) | -0.011** (0.005) | -0.076*** (0.024) | 0.005*** (0.002) |
| Access to electricity | 0.685*** (0.189) | -0.013*** (0.004) | -0.077*** (0.017) | 0.005*** (0.001) |

Note: ****p-value* < 0.01, ***p-value*<0.05, **p-value*<0.1, standard errors in parenthesis

Additionally, although Indonesia is highly vulnerable to natural disasters such as flooding, certain regions frequently experience droughts due to a lack of precipitation. This condition may impact water availability for agricultural, drinking, and sanitation purposes. In areas dependent on rain-fed agriculture, insufficient precipitation can lead to crop failures, severely impacting food production and availability. The decline in agricultural productivity not only threatens food security but also exacerbates poverty levels, as many rural communities rely on agriculture for their livelihoods.

The findings of this study underscore the multifaceted and complex relationship between climate change and multidimensional poverty in Indonesia. However, the impacts largely depend on the local context, the effectiveness of management strategies, and the ability to adapt to and cope with these challenges. For instance, in regions that rely heavily on agriculture, such as Papua and West Papua provinces, extreme temperature increases and droughts may reduce labour productivity, thereby lowering agricultural output and income. On the other hand, regions with stronger adaptive capacities—such as improved infrastructure in the western region of Indonesia—may experience less severe consequences from climate change.

## CONCLUSION

This paper develops an alternative measurement of multidimensional poverty using the capability approach and explores the relationship between climate change and multidimensional poverty in Indonesia, utilizing secondary data from 33 provinces between 2010 and 2020. The findings show a general reduction in poverty across most provinces over the past decade. In 2010, approximately 57 percent of the provinces had high poverty levels, with MPI scores above 0.5. By 2020, almost all provinces had reduced their poverty levels below 0.5, except for Papua, which showed minimal improvement. The robustness of the MPI estimates for each province was confirmed.

Additionally, this study incorporated historical temperature and precipitation data for each province from 2010 to 2020 to assess their relationship with the MPI. The results reveal a significant non-linear relationship between temperature and precipitation, as well as multidimensional poverty. Temperature is associated with the MPI in a U-shaped manner, while precipitation is in an inverted U-shape.

Based on these findings, the government should focus on adaptation strategies tailored to regional conditions. Integrating multidimensional poverty measures into climate change policies is essential to address not only economic but also health, education, and housing dimensions of poverty. Investing in climate-resilient infrastructure and improving access to essential services will help reduce climate-induced disparities, thereby lowering the MPI. Promoting early warning systems and climate education will help reduce climate-induced losses, thereby decreasing the MPI in regions relying on natural resource-based livelihoods, such as agriculture and forestry, particularly in Papua and West Papua, where temperature is expected to increase while precipitation becomes increasingly unpredictable due to climate change.


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