Socio-Spatial Analysis of Poverty: A Comprehensive Study on Integrating Multidimensional Poverty Indices with Geographic Conditions in Krucil District, Probolinggo, Indonesia

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Submitted: 20 March 2024. Accepted: 10 October 2024. Published: 31 October 2024
Volume 33, 2025. pp. 651–668. http://doi.org/10.25133/JPSSv332025.035

Abstract

The role of geography in population studies is represented by the utilization of space in studying social issues. The study explores the intersection of geography and population studies by employing spatial analysis to examine social problems, particularly poverty. Focusing on the Krucil District in Probolinggo Regency, East Java, Indonesia, the research integrates multidimensional indicators of well-being to provide a comprehensive understanding of poverty. The Multidimensional Poverty Index (MPI) is a comprehensive poverty measurement tool at the individual and household levels. The urgent integration of spatial analysis into social sciences is essential for addressing the significant poverty level as a socioeconomic problem. Poverty measurement was analyzed using the Alkire-Foster (AF) method with primary data from 132 households across 11 sub-districts. Results reveal the MPI score of 0.19, indicating significant poverty levels, with the health dimension most affected. Moran's index of -0.134, indicating no spatial autocorrelation (p value > alpha, .574 > 0.05), suggesting that high multidimensional poverty areas are surrounded by low poverty areas and vice versa, with geographic, spatial, and physical conditions significantly contributing to multidimensional poverty. These findings suggest that poverty alleviation efforts commence with Seneng Village, which has been designated as a pilot project. This approach will allow for the testing and refinement of strategies in a controlled environment, providing valuable insights and data that can be applied to broader initiatives.

Keywords

Geographical condition; local indicator of spatial analysis (LISA); Multidimensional Poverty Index; poverty deprivation; socio-spatial analysis

Introduction

Fulfilling basic needs and rights is a key objective within the Social Development Pillar of the Sustainable Development Goals (SDGs), aiming to comprehensively enhance societal welfare. Poverty remains a critical social issue today, closely aligning with the first goal of the SDGs, which seeks to eradicate all forms of poverty, eliminate hunger, and ensure health and prosperity. Poverty is when individuals face undesirable limitations (Swastika & Supriyatna, 2016). The BPS-Statistics Indonesia (2011) defined poverty as the inability to satisfy basic living requirements, which is marked by low income and the failure to cover essentials like food, clothing, and housing. Furthermore, this low income also hinders achieving average living standards in health and education (Deffinika et al., 2022). Understanding the complex nature of poverty and its connection to the SDGs, particularly SDG 1, is crucial for designing effective solutions. From a demographic perspective, poverty is seen as both a social and economic problem that remains a priority to be addressed in various countries worldwide.

The disruption caused by the COVID-19 crisis has increased the number of people living in poverty. The global extreme poverty rate reached 9.3%, up from 8.4% in 2019 (World Bank, 2022). Poverty can be considered a problem from various scientific points of view, and the causes of poverty can be examined from multiple sectors. One of the main goals of the SDGs is to address these issues comprehensively. The Indonesian local government, for example, has adapted its goals and indicators related to poverty eradication programs, aiming to reduce by at least half the proportion of men, women, and children of all ages living in poverty in all its dimensions according to national definitions by 2030 (UNICEF, 2022). This demographic approach highlights the importance of tailored strategies to combat poverty effectively, ensuring that all population segments are considered in these efforts.

Poverty encompasses various aspects, reflecting the diverse needs of humans. It includes primary elements such as a lack of assets, socio-political organization, knowledge, and skills, and secondary aspects like a lack of social networks, financial resources, and information. Poverty can be analyzed from multiple perspectives. While it is often viewed from an economic standpoint, poverty measurement can be conceptually linked to various factors, including absolute and relative poverty. These concepts are widely utilized in research and academic studies. Relative poverty assesses an individual's economic status compared to their broader society. It highlights inequalities and social exclusion by focusing on the inability to maintain a standard of living similar to the majority.

The general poverty measurement could be done using perspectives or indicators based on global indicators. The Indonesian government measures poverty using the capacity concept to meet basic needs or the basic needs approach. This approach explains that poverty is considered an economic inability to meet basic food and non-food needs when measured in spending (Adji et al., 2020). People are considered poor if their average monthly expenditure per capita is below the poverty line. Expenditure-based measures are still considered inadequate to describe the state of poverty holistically, given that approaches to poverty reduction can be considered from multiple perspectives. People who live in poverty are socio-economically vulnerable or disadvantaged. For example, they are at high risk of dying due to poor access to health care. Economic inequality is also related to social and spatial dimensions.

The United Nations (2020) showed that economic inequality is generally greater in urban than rural areas, with 36 of the 42 countries having data having high Gini coefficients of income inequality in urban areas. Societies with high inequality are less effective at reducing poverty than societies with low inequality. They also grow slowly and are less successful at sustaining economic growth. Disparities in health status and education make it difficult for people to escape the cycle of poverty, especially in developing countries like Indonesia (Kurniawan & Kuncoro, 2016)—Human Development Index linkage with poverty condition (Singh, 2012). A high level of the Human Development Index has implications for the success of the poverty reduction program. Indonesia’s poverty rate experienced a slight decrease, both in terms of numbers and percentages. The number and rate of poverty-induced poverty varies. This has happened recently after soaring prices for essential commodities due to rising fuel prices and also at a time when there were restrictions on population movement during the COVID-19 pandemic that hit Indonesia.

The problem of poverty can be explored in a multidimensional framework. Therefore, poverty is not only related to income measurement, but it involves several things, including (i) the vulnerability and susceptibility of people or communities to becoming poor and (ii) the presence/absence of fulfillment of the fundamental rights of citizens and the presence/absence of differences in the treatment of a person or group of people in living life in a dignified manner (Turriago-Hoyos et al., 2020). The Ministry of Finance of the Republic of Indonesia (2018) stated that one of the strategies that could be taken to break the poverty cycle is to develop the quality of human resources (HR). Indonesia's economic growth and Human Development Index continue to increase; however, the increase is not parallel with the poverty rate, which does not decrease significantly (Fuady et al., 2021).

While poverty has multiple dimensions, it is often measured by income levels. The World Bank Group (2024) defines extreme poverty as living on less than US$1.90 per day, while moderate poverty is living on US$3.10 per day. Using these definitions, over 700 million people live in extreme poverty globally, concentrated primarily in sub-Saharan Africa and South Asia (Khan & Sloboda, 2023). The complexity of the poverty measurement makes poverty alleviation better measured based on expenditure and assessed using a multidimensional approach (Dong et al., 2021). The Multidimensional Poverty Index (MPI) was designed to compare overall deprivation levels in an area (Khaliq & Upsri, 2017; Lange, 2021).

The multidimensional poverty concept arises when the measurement of poverty based on income is not representative enough to reveal a household’s socioeconomic condition. The results of previous studies show that people who experience multidimensional poverty are deprived of at least three poverty indicators, namely education, health, and living standards (Aidha et al., 2020; Alkire & Foster, 2011; Alkire et al., 2015; Alkire & Santos, 2014; Chzhen et al., 2018) Indonesian poverty disparity between urban and rural areas is striking. Globally, rural areas have significantly higher poverty rates than urban areas, highlighting a crucial gap in living standards and resource access (Jha & Tripathi, 2023). This phenomenon affects regions worldwide, although specific figures and contributing factors may differ. The number of poor people in urban areas is 11.98 million, or around 7.6%.

In comparison, the number of poor people in rural areas is 14.38 million, or around 12.36% (BPS-Statistics Indonesia, 2022). An estimated 8.17% of the total population in Indonesia is experiencing multidimensional poverty living. This means that there are 21.5 million people who could not achieve certain minimum thresholds in various dimensions, such as health, education, and living standards (Aidha et al., 2020; BPS-Statistics Indonesia, 2022). The highest percentage of Indonesia’s poor population, both urban and rural, is still concentrated on Java

Island. East Java has become one of Indonesia's three provinces with the highest multidimensional poor population.

East Java Province in 2021 was classified as a province with a relatively high number of extremely poor populations. Based on expenditure calculation, the number of poor people in East Java Province experienced an increase from 4.112 million people in 2019 to 4.419 million in 2020 and 4.527 million in 2021 (BPS-Statistics Indonesia, 2022). Meanwhile, compared poverty data examined using a multidimensional approach, the number of multidimensional poor people in East Java Province reached 9.47% or 1.044 million.

To address the challenges of achieving SDGs Goal 1, the Indonesian government has been prepared for a poverty reduction program by forming The National Team for the Acceleration of Poverty Reduction (TNP2K). In 2021, TNP2K revealed that five priority districts in East Java Province have many extremely poor people: Probolinggo Regency, Bangkalan Regency, Sumenep Regency, Probolinggo, and Lamongan. Poverty conditions in the Probolinggo Regency took first place with the highest percentage of the Multidimensional Poverty Index (MPI) in East Java Province, which was 14.78%. In addition, it is also the third highest extreme poverty position. It has a poverty rate of 18.61%, while the extreme poverty rate reaches 9.74%, with the number of extremely poor people reaching 114,250 people. This number has increased from 2018 to 2021 by around 3%. Probolinggo Regency was classified as the top third district in terms of extreme poverty in the population in 2021 (Aidha et al., 2020).

Poverty assessment has relied heavily on single-dimensional measures, often focusing solely on income levels. However, this approach fails to capture poverty's complexity and multifaceted nature, leaving many vulnerable individuals and communities unseen. Poverty alleviation is seen as a multidimensional problem. It has been realized that poverty is an economic, spatial, and social problem. Thus, spatial integration in overcoming the issue of poverty with its various dimensions will minimize the risk of destructive impact that leads to social, economic, security, legal, and political instability. It often affects the existence and resistance of a government on a local, regional, national, and even international scale (Great Britain Department for International Development [DFID], 2008). Therefore, a study on poverty by integrating multidimensional poverty and spatial approach was carried out to analyze the current Multidimensional Poverty Index (MPI) conditions based on spatial and socioeconomic data conditions. The outcome could be a reference for policy decision-making systems to reduce poverty. It is hoped that poverty alleviation can be overcome equally in various aspects.

The reduction of multidimensional poverty in Indonesia is inseparable from the contribution of development programs launched by the government. For example, increased budget allocations for health, education, and social protection have also accelerated poverty reduction. The acceleration of the government's social programs is also more evenly distributed, as seen from the increase in beneficiary households of the Family Hope Program (PKH) and Contribution Assistance Recipients (PBI) in the National Health Insurance (JKN) program. In addition, there has been a progressive improvement in basic infrastructure, such as developing community-based sanitation and public housing. This action requires collaboration from practitioners and academics. The critical point of multidimensional poverty reduction in Indonesia is systematic cooperation between the central government and local government related to poverty alleviation program implementation. Studies on poverty require collaboration between practitioners and academics. As Batty and Orton (2018) asserted, the social welfare management system to prevent poverty must be improved; therefore, a study about integrating multidimensional and spatial approaches was carried out to analyze the current Multidimensional Poverty Index (MPI) conditions based on spatial and socioeconomics data conditions.

Method

Research approach

Spatial analysis in multidimensional poverty involves examining the spatial distribution and patterns of poverty across different dimensions or aspects of well-being within a geographic area. It was carried out using poverty reduction modeling based on geospatial data processing. The approach used in this study is quantitative. The poverty was measured using the Alkire-Foster (AF) method based on the Multidimensional Poverty Index (MPI).

Research location

This research location was chosen in East Java, Indonesia, as one of the government's priority targets in the Extreme Poverty Eradication Program 2024 (TNP2K, 2021). Probolinggo Regency is in the top third rank in terms of extreme poverty. Until 2021, it was recorded that there were 114,250 residents, or equivalent to 9.74% of the total population of Probolinggo Regency, experiencing extreme poverty. This makes Probolinggo Regency the study location (Cabinet Secretariat of the Republic of Indonesia, 2021; TNP2K, 2021). Reducing extreme poverty in Probolinggo Regency begins with a study in five sub-districts as a pilot project. One of the pilot projects of the program to eliminate extreme poverty is Krucil Subdistrict (Mujiono, 2021).

Data processing and analysis

This research uses primary data to assess socioeconomic characteristics and MPI. This is also supported by secondary data from BPS-Statistics Indonesia and geospatial data from Ina-Geoportal (Geospatial Information Agency, 2024). The BPS-Statistics Indonesia (2022) clarified that three dimensions must be considered when calculating the Multidimensional Poverty Index (MPI): education, health, and living standards. The three dimensions have measurement indicators used as variables in this study. Each dimension is considered to have an equal contribution to household poverty; however, the number of indicators for each dimension differs. The weight of each indicator can be seen in Table 1.

Table 1: Weight of Indicators of Multidimensional Poverty Assessment

Dimension	Deprivation Indicator	Weight	Cut-off
Health	Sanitation	1/9	0: has a private and communal toilet
			1: Doesn't have private and communal toilet
	Drinking water	1/9	0: drinking water from bottled water, tap water, and pump
			1: Does not use drinking water from pumps, protected wells that are < 10 meters from a septic tank
	Under-five Nutrition	1/9	0: meets the minimum nutrition based on age group 0–1; 1–3; and 35 years old.

Dimension	Deprivation Indicator	Weight	Cut-off
			1: Doesn't meet the minimum nutrition based on age group 0–1; 1–3; and 3–5.
Education	Early Childhood Education	1/6	0: have access to preschool or kindergarten
			1: Doesn't have access to preschool or kindergarten
	School	1/6	0: Able to complete their education up to senior high school
			1: Primary and secondary school age who are unable to complete their education up to senior high school
Living Standard	Light Source	1/9	0: Use electricity from National Electric Company
			1: Doesn't use electricity from National Electric Company
	Cooking Fuel	1/9	0: Use cooking fuel from gas or electricity
			1: Use cooking fuel from kerosene, charcoal, brackets, and firewood.
	Housing condition	1/9	0: Have no unfit or at least one condition from two of the three sub-indicators
			1: at least an unfit condition for two of the three sub-indicators

Each indicator in the health dimension is weighted as 1/9; Each indicator in the education dimension is weighted as 1/6; and Each indicator in the living standard is weighted as 1/9. The deprived indicator score is (1: Deprived; 0: Not Deprived). The Alkire-Foster method was used to calculate Indonesian SMEs by calculating deprivation of health, education, and living standards. Modifications of several indicators were carried out in the calculation of MPI by adjusting the context and conditions in Indonesia.

Spatial analysis was carried out using spatial autocorrelation (SA) to measure the association between the MPI scores of nearby units. The SA was evaluated using the Moran's I index. In this study, SA was done using a local indicator of spatial association (LISA) technique, and the units were sub-districts of the Krucil District. A positive score of spatial autocorrelation indicates that areas with similar attribute values are located close to each other. In contrast, negative score spatial autocorrelation indicates that counties with different attribute values are close to each other. There is no spatial association if the spatial autocorrelation is close to zero. As with Pearson's correlation, this can be assessed using a hypothesis test.

Results and discussion

Multidimensional Poverty Index in Krucil district

The Multidimensional Poverty Index (MPI) is a comprehensive poverty measurement tool at the individual and household levels. The MPI could be used to monitor the progress of the achievement of SDG Goal 1, aiming to end all forms of poverty everywhere. The UNDP stated that expanding poverty indicators and using a multidimensional approach is an initial strategy in the global poverty reduction framework (Dieye, 2019). The poverty issue has been trapped in a narrow range indicator. This impacts the ineffectiveness of poverty reduction programs (Kurniawan & Kuncoro, 2016).

The MPI gives information about comprehensive measurement of poverty that will encourage policymakers to issue relevant policies following the root causes of poverty experienced (Lanau et al., 2020). The result of MPI measurement in Krucil District can be seen in Figure 1.

Figure 1: Diagram Information of Overall MPI Component in Krucil District

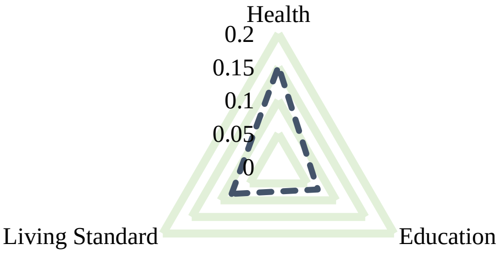


Diagram	Information	Score
(see diagram above)	Health Dimension	0.151
	Education Dimension	0.068
	Living Standard Dimension	0.081
	H	0.50
	A	0.37
	MPI	0.19

Figure 1 shows the results of the poverty index calculation. It is shown that the MPI score of the Krucil District is 0.19. This means that 19% of the population in the Krucil District is deprived of education, health, and living standards—the H score represents a multidimensional poverty ratio. The Krucil's H score is 0.5, meaning that half the Krucil population is affected by multidimensional poverty—the intensity of multidimensional poverty represented by the A score. The Krucil's A score is 0.37. This number describes the average deprivation score or percentage of dimensions in which poor people are deprived. This number also indicates that it causes population deprivation. This means that the population of Krucil, which experiences multidimensional poverty, is deprived of around four out of 10 indicators collected in the MPI calculation.

Looking at Figure 1, the health dimension has the largest number of deprivations compared to the other two dimensions, which is 0.151. It can also be interpreted that the health dimension contributes the most to the number of deprived poor populations in Krucil. Then, the standard of living dimension was followed by a score of 0.081, and the education dimension was scored at 0.068. It is well known that socioeconomic status and health are closely related. Numerous studies have discovered, among other things, that lower wealth is linked to worse health (Lorant et al., 2003; Oshio, 2014; Zimmerman & Katon, 2005). This is most likely also true of health, which can be expected to be influenced by several aspects of poverty rather than solely linked to one. Indeed, the relationships between health and many socioeconomic determinants have received increased attention (Bartley, 2016; Marmot, 2005). Poverty deprivation based on indicators in the Krucil District is shown in Figure 2.

Figure 2 describes the source of deprivation in three dimensions.

Figure 2: MPI Based on Dimension

Dimension	Deprivation Indicator	% of Total MPI
Health	Sanitation	0.00%
	Drinking water	36.47%
	Under-five Nutrition	16.18%
Education	Early Childhood Education	7.94%
	School	7.65%
Living Standard	Light Source	0.00%
	Cooking Fuel	10.59%
	Housing condition	21.18%

Health dimension

The health dimension score of Krucil Districts is 0.151. The sub-district with the highest Health dimension score is the Krobungan sub-district, with a score of 0.198, while the lowest score of 0.125 belongs to the Tambelang sub-district. This score indicates the proportion of individuals in a given population deprived of health-related indicators. The health dimension of the MPI typically includes various health indicators, such as access to clean water, sanitation, nutrition, child mortality, and maternal health, among others. A health MPI score of 0.198 means that approximately 19.8% of the population experiences deprivation in health-related indicators. This deprivation can manifest in various forms, such as lack of access to clean drinking water, inadequate sanitation facilities, insufficient nutrition, high child mortality rates, or limited access to maternal healthcare services. It is important to note that the MPI provides a multidimensional understanding of poverty, considering different aspects of well-being beyond just income or consumption. By incorporating health indicators into the index, policymakers can identify areas where interventions are needed to improve health outcomes and comprehensively reduce poverty. In the dimension of Health itself, three indicators serve as a reference to determine the score of these dimensions:

Sanitation indicator

Sanitation Indicators can be deprived if a person does not have public, shared, or private defecation facilities and the toilet is not a goose-neck type. The results showed that all samples in the Krucil District had access to good sanitation. The need for essential water and sanitation services assumes even greater significance when the linkages with other dimensions of poverty are considered (Bosch et al., 2001). Human waste poses a tremendous social cost through the pollution of rivers and groundwater.

Drinking water indicator

Deprived of drinking water indicator addressed to households that consume clean water that does not come from metered and retail taps, do not use drinking water from pumps, protected wells/protected springs that are > 10 meters from the septic tank. This assumption is used because if the protected spring is < 10 meters from the septic tank, there is a possibility that drinking water can be contaminated with elements from the septic tank, either in solid or liquid form. Figure 1 shows that over 90% of the sample is deprived of poverty. Water and sanitation-related sicknesses put severe burdens on health services and keep children out of school (Bosch et al., 2001; Ghosh et al., 2022). One critical global public health development key factor is access to untreated drinking water sources.

Under-five nutrition

As shown in Table 2, this indicator classified deprived people as having a nutritional intake below the required threshold. The minimum nutritional needs of children under five based on age group under 1 year, 1–3 years, and 4–5 years have been regulated by the Minister of Health of Indonesia regulation number 75 of 2013 concerning the Recommended Nutritional Adequacy Rate for the Indonesian Nation.

Table 2: Indonesian Energy Consumption Classification Based on Age Groups

Age Group (in years)	Energy (kcals)
< 1	637.5
1–3	1.125
3–5	1.600

Note: Based on Aidha et al. (2020)

The statistic indicating that 41.67% of households in the Krucil Sub-district are classified as deprived highlights a significant portion of the population facing challenges in meeting basic needs and accessing essential resources. Among these needs, adequate nutrition is crucial in improving human resources' quality, health, cognitive development, and overall well-being (Ainistikmalia et al., 2022; Aprilia et al., 2022). Given the significant proportion of deprived households in the Krucil Sub-district, addressing nutrition-related challenges through targeted interventions such as nutritional education, food assistance programs, access to affordable and nutritious foods, and community-based health initiatives becomes crucial. By improving access to adequate nutrition, communities can enhance the quality of their human resources, leading to better health outcomes, economic development, and overall well-being.

Education dimension

Education is compulsory and constant, especially for children, because it strongly relates to their future income and life. However, access to quality education is still not evenly distributed (Treanor, 2020), including in the Probolinggo District—the score for the Education dimension in the Krucil District is 0.068. The score on this dimension is the smallest contributor to the final MPI score in the Krucil District. This score indicates that approximately 6.8% of the population is deprived of education-related indicators. This deprivation could be due to limited access to schooling facilities, low enrollment rates, high dropout rates, or poor quality of education. By incorporating education indicators into the MPI, policymakers can gain insights into the education-related dimensions of poverty and prioritize interventions to improve access to and quality of education, thereby contributing to poverty reduction and human development. The sub-district with the highest education score is Krobungan, which is 0.167. To measure the dimensions of Education in the Multidimensional Poverty Index, several indicators are needed, namely:

Early childhood education indicators

Individuals (children) are said to be deprived of those aged 3–6 years who do not have access to preschool education services, such as early childhood education, other PAUD equivalent posts, kindergarten or its equivalent, play groups, and other preschools. As much as 20.45% of households are classified as deprived. This deprivation is experienced due to the well-known that parental educational attainment is strongly associated with many positive externalities for other household members, including children (Dirksen & Alkire, 2021).

School sustainability indicators

Individuals (children) are said to be deprived if they are at primary and secondary school age and are unable to complete their education to senior high school. Deprived households in this indicator experience as much as 19.7%. Such indicators are imprecise approximations of children's actual deprivations and rely on the association between children's and others' deprivations or achievements (Dirksen & Alkire, 2021). Additionally, the connection between household employment status and children's education is highlighted, suggesting that decent opportunities within households can contribute to improved educational outcomes for children. However, households facing livelihood vulnerabilities may struggle to support children's education adequately, further exacerbating deprivation in this dimension.

Living standard dimension

Various types of rural public expenditure impact rural poverty differently, depending on the spending sector, the targeting effectiveness, and the financing methods. The effects also vary based on the poverty reduction approach; some expenditures directly impact poverty, such as social security, while others, like health, education, infrastructure, and living environment, have more indirect effects (Liu et al., 2020). The standard of living dimension is the last dimension used to analyze MPI. In Krucil District, the standard of living dimension has a score of 0.081. The Guyangan sub-district became the sub-district that contributed the highest score for this dimension. Households with better living standards increase the opportunity for economic material (Li et al., 2022; Wang et al., 2022). To see the dimensions of the standard of living, there are three indicators are used, namely:

Light source

A deprived household is classified if they use electricity for lighting that is not from State Electricity Company/PLN, such as Petromax/Aladdin, lamp/flashlight/torch, or other lighting sources. The results showed that all samples in the Krucil District had access to electricity.

Cooking fuel

A person is said to be deprived if they use fuel for cooking that uses electricity and gas as fuel for cooking, such as kerosene, charcoal, brackets, and firewood—households with cooking fuel deprived as much as 27.27%.

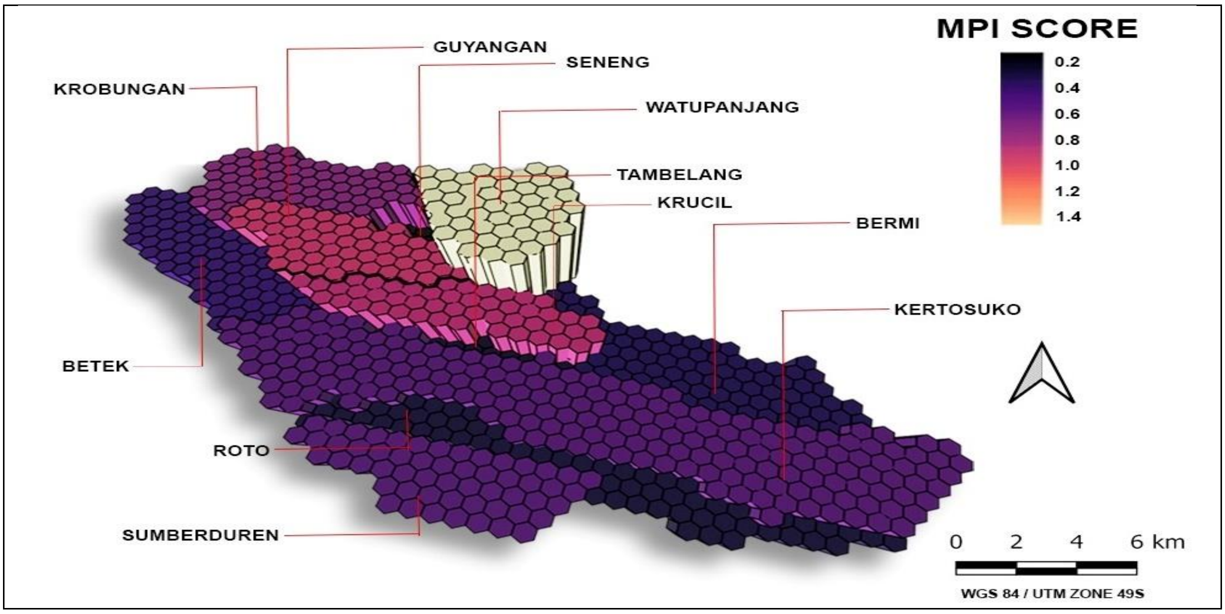
Housing condition of the wall, roof, and floor

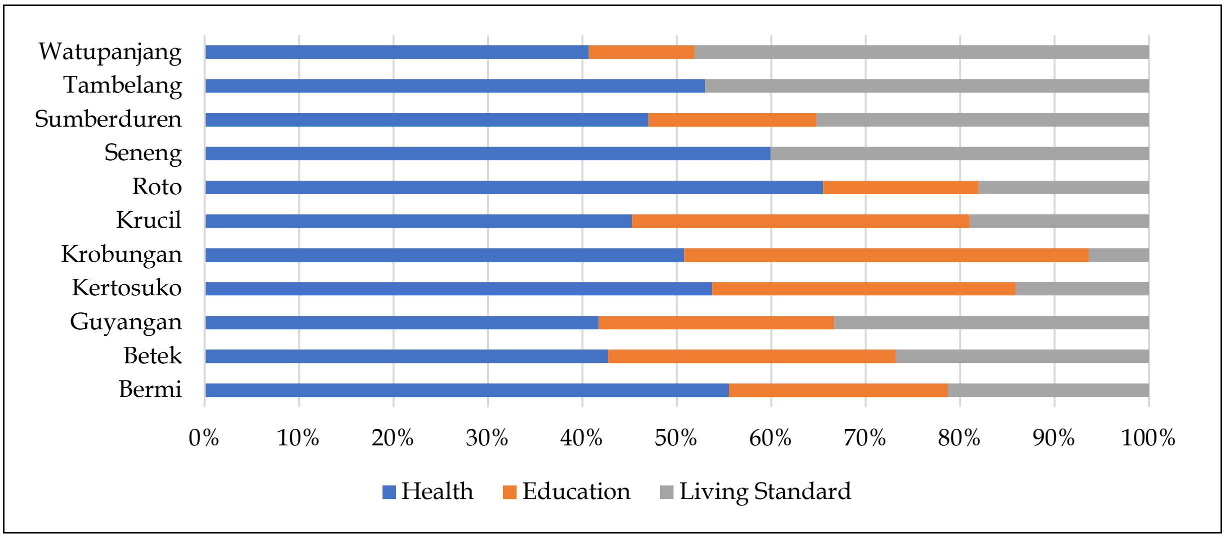
A person deprived of this indicator has at least two sub-indicators (roof, floor, and wall) conditions that are not feasible. The roof of a house that is said to be unfit is a roof made other than concrete, tile, zinc, and asbestos, such as bamboo, wood/shingle, straw/leaves, and others. The floor of the house is said to be unfit if the floor is made of other than marble, ceramic, granite, tile, terrazzo, cement, and wood, such as bamboo, low-quality wood/board, soil, and other materials. The house's walls are said to be unfit if the floors are made of other than walls and wood, such as woven bamboo, logs, bamboo, and other materials—households with cooking fuel deprived as much 54.55%.

Spatial distribution of MPI

Analyzing the spatial distribution of the Multidimensional Poverty Index (MPI) involves mapping the prevalence and severity of poverty across different geographic units, such as regions, districts, or communities. Gather relevant data on multidimensional poverty indicators for each geographic unit. These indicators may include education, health, living standards, and other dimensions that reflect various aspects of well-being. Poverty also manifests as spatial self-reinforcement (Luo et al., 2021). Spatial Aggregation and visualization show MPI values at a suitable geographic level, such as administrative boundaries or grid cells, to create a spatial dataset representing the distribution of poverty. Geographic Information Systems (GIS) software or mapping tools can be used to visualize the spatial distribution of the MPI. This can be done by creating choropleth maps, where different colors or shades represent varying poverty levels across geographic units (Rinner, 2018). The spatial distribution of MPI is shown in Figure 3.

Figure 3: MPI Score Dimensions in the Krucil District



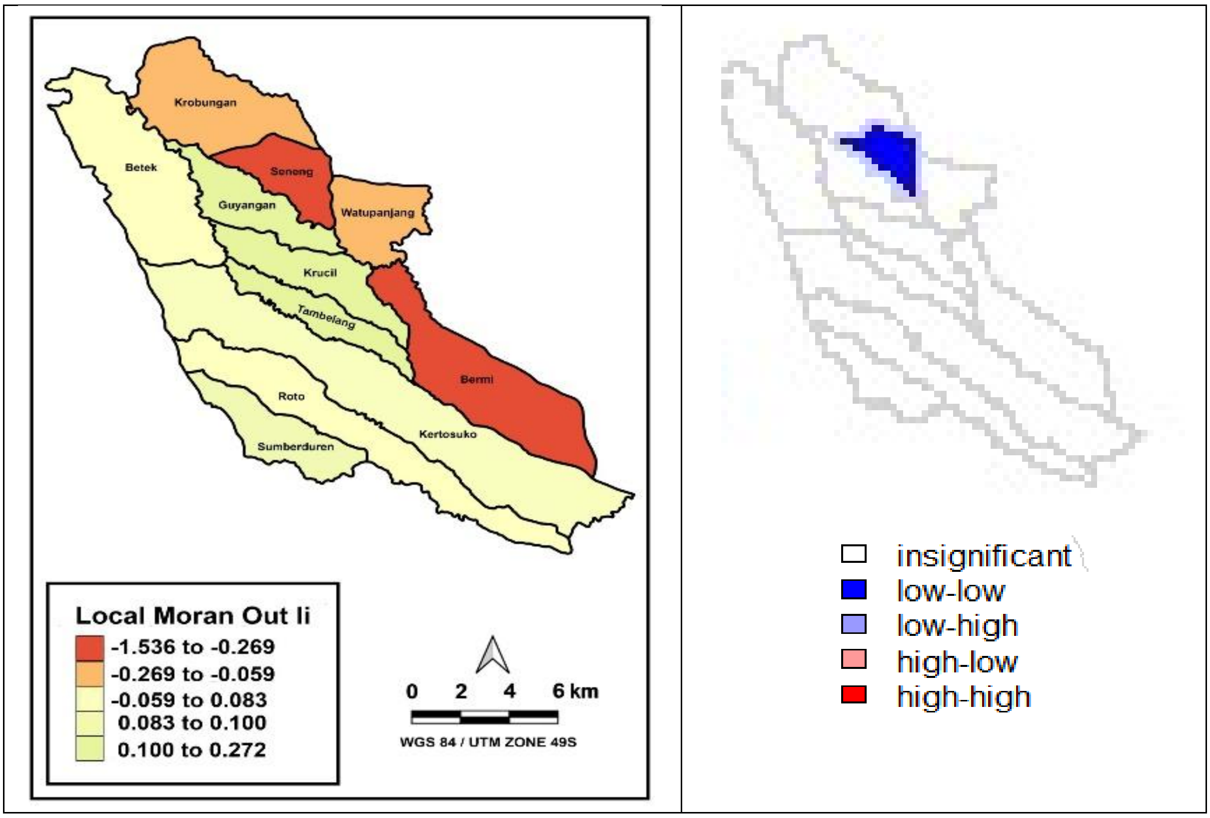


The study has demonstrated and emphasized the spatial distribution pattern of poverty, which is valuable for planning and guiding policy formulation to eradicate poverty (Majid et al., 2016). Spatial differences in the Multidimensional Poverty Index (MPI) refer to variations of multidimensional poverty rates across different regions or spatial locations. It reflects a situation where poverty rates and the associated dimensions vary from region to region. Neighboring villages exhibit higher similarity in values compared to more isolated ones. Poor and non-poor adjacent villages tend to form clusters due to their spatial structure (Ari et al., 2021).

Spatial differences in the MPI indicate regional differences, differences between population groups, differences between living environments, and differences between geographic conditions. Understanding spatial differences in MPI is vital for designing effective policies to address poverty and social inequality. It allows policymakers to identify the most vulnerable areas or population groups and formulate intervention strategies that suit the needs of each region or group.

Figure 3 reveals spatial differences of the MPI in the Krucil District. Despite spatial differences, the health dimension is a significant issue in Krucil's overall MPI. This is due to the low quality of health dimension, which not only affects an individual's quality of life directly but can also be a cause or effect of many other poverty factors. Health is often measured through indicators such as child mortality, access to clean water and sanitation, attendance at health services, and prevalence of communicable diseases (Aiyar & Sunder, 2024; Deffinika et al., 2020). The inability to meet these basic needs can lead to individuals and families being trapped in multidimensional poverty.

Figure 4: Local Distribution Map of Moran's & Local Indicators of Spatial Association (LISA) Cluster



Geographic Data Analysis was used to identify spatial data analysis through Spatial autocorrelation (SA), which denotes the positive and negative of a variable correlation with itself in spatial location (Farahani et al., 2010). The positive value describes similar spatial clusters of high-high or low-low. The negative indicates different values of spatial outliers of high-low or low-high. Six sub-districts are shown to have a positive value, which means that poverty in these sub-districts is related. While the other five are indicated to have a negative value, which means that poverty in these sub-districts is not associated with each other.

The SA is used to help identify patterns of similarity or dissimilarity in the distribution of the variable across geographic space. In six sub-districts, spatial autocorrelation had a positive value. This suggests that the levels of poverty in these sub-districts are spatially clustered. Specifically, the positive value indicates the presence of high-high or low-low spatial clusters. High-high spatial clusters refer to sub-districts where high poverty levels are clustered together, while low-low spatial clusters indicate sub-districts with low levels of poverty clustered together. The positive spatial autocorrelation implies a spatial dependency or similarity in the distribution of poverty across these sub-districts.

In the other five sub-districts, spatial autocorrelation had a negative value. This suggests that the levels of poverty in these sub-districts are not spatially related to each other. The negative value of spatial autocorrelation indicates the presence of spatial outliers or dissimilarities in the distribution of poverty across these sub-districts. Specifically, it suggests the presence of high-low or low-high spatial outliers. Sub-districts with negative spatial autocorrelation may have unique characteristics or factors contributing to their poverty levels, differentiating them from neighboring areas. Overall, the findings provide insights into the spatial patterns of poverty within the region, highlighting areas of spatial clustering and outliers. Understanding these spatial patterns can inform targeted interventions and policies aimed at addressing poverty and promoting equitable development across different sub-districts

Figure 4 shows information about the Moran's index value. The Moran's index for multidimensional poverty in the Krucil District is -0.134. A negative Moran's index value indicates the presence of negative spatial autocorrelation. Negative spatial autocorrelation suggests that areas with low multidimensional poverty and vice versa surround areas with high multidimensional poverty. In other words, there is a tendency for dissimilar values to be clustered together spatially. The hypothesis testing yielded a p of .574, greater than the significance level (alpha) of 0.05. With a p value greater than alpha, the null hypothesis (H0) is accepted, indicating no significant spatial autocorrelation. Overall, the combination of the negative Moran's index value and the acceptance of the null hypothesis suggests that no significant spatial autocorrelation exists in the distribution of multidimensional poverty in the Krucil District. However, the negative Moran's index value still provides valuable information about the spatial patterns of multidimensional poverty, indicating the presence of clustering or dispersion of poverty across different areas within the district.

Figure 4 shows that Seneng Village is included in cold spots (LL). Areas included in cold spots have low multidimensional poverty rates but are adjacent to areas with low multidimensional poverty rates (Dong et al., 2021; Jha & Tripathi, 2023). This result is per the local value of Seneng Village Moran's index, which is only -1.536. The spatial distribution of multidimensional poverty in the Krucil District is random. This means there is no statistically significant spatial clustering of poverty levels; however, the negative value of Moran's index is still relevant, as it suggests spatial dispersion or an outlier pattern. Understanding the spatial distribution of poverty can aid policymakers and local governments target interventions more effectively (Dong et al., 2021; Majid et al., 2016). Identifying cold spots like Seneng Village allows for resource allocation and policy interventions to be directed towards maintaining or enhancing the conditions that lead to low multidimensional poverty. Conversely, areas not identified as cold spots or with higher multidimensional poverty rates can be targeted for development programs, infrastructure improvements, or social support mechanisms to help reduce poverty levels.

Conclusion

The intersection of geography and population studies is crucial in addressing complex social issues such as poverty, particularly in regions with unique spatial dynamics like Krucil District, Probolinggo Regency, East Java, Indonesia. This study underscores the necessity of integrating spatial analysis with social sciences to gain a nuanced understanding of poverty distribution and its underlying causes. The alarming Multidimensional Poverty Index (MPI) score of 0.19 highlights significant poverty levels, with the health dimension being the most severely impacted. Moran's index of -0.134 indicates that the lack of spatial autocorrelation reveals a complex spatial distribution of poverty that demands immediate attention.

Given the substantial role that geographic, spatial, and physical factors play in shaping multidimensional poverty, it is imperative to prioritize targeted interventions. The proposed pilot project in Seneng Village is an urgent first step. By focusing on this area, we can develop and test effective poverty alleviation strategies, ensuring they are well-suited to the region's unique geographic and social conditions. The insights gained from this pilot project will be critical for scaling up efforts across other areas, ultimately contributing to more effective and sustainable poverty reduction initiatives in Indonesia.

Spatial integration is not just about adding a map to poverty analysis. It is about leveraging spatial information to uncover more profound injustices and empower effective solutions toward a more equitable world. Assessing poverty using a multidimensional approach gives information about the comprehensive measurement of poverty. Integrating the Multidimensional Poverty Index towards the spatial decision support system (SDSS) is carried out by mapping spatial and socioeconomic data. The overall MPI score of the Krucil District is 0.60. The health dimension deprivation has the largest number compared to the other two dimensions, which is 0.151—then, followed by the standard of living dimension with a score of 0.081 and the education dimension with a score of 0.068. This means that health awareness in Krucil District is still relatively low compared to education and living standards. Geographically weighted regression tests showed good significance with a p of .008. Slightly different from the correlation test results, the dimensions of education and living standards have a significant relationship in this OLS test. The Education dimension has a p of .042, the Standard of Living dimension has a p of .001, and the Health dimension has a p of .246. Therefore, the Health dimension is insignificant to the poverty index in Krucil District.

Generally, Moran's index on multidimensional poverty in the Krucil District shows a value of -0.134. A negative value on the Moran's index indicates no negative spatial autocorrelation. While the results of hypothesis testing accept $H_{0,}$ there is no spatial autocorrelation with p > *alpha*, where .574 > 0.05. Negative spatial autocorrelation values indicate that areas with low multidimensional poverty and vice versa surround areas with high multidimensional poverty. Geographic, spatial, and physical conditions have contributed to multidimensional poverty. Poverty alleviation through population policy such as the Grand Design of Population Development should involve local government. Poverty is often measured solely based on material indicators such as income and access to basic needs. However, Sen's Capability Approach highlights the importance of an individual's ability to achieve various functions they value. Suggestions for further research and analysis to integrate Sen's Capability Approach with the Multidimensional Poverty Index (MPI) by Alkire and Foster (2011) will help us obtain a more comprehensive measure of poverty. This integration considers the multidimensional aspects of deprivation and the significance of individual capabilities in assessing well-being, providing a more holistic view of poverty and quality of life.

Acknowledgments

The author would like to thank Universitas Negeri Malang for supporting research funding in Hibah Internal Non-APBN, which made this research possible. The contents of this article are the sole responsibility of the author.

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