COMMUNICATIONS IN
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Granular multidimensional poverty index using grid-based spatial modeling: A case study of East Java, Indonesia

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Article history:
Received: 6 August 2025 / Received in revised form: 17 December 2025 / Accepted: 18 December 2025

Abstract

Capturing multidimensional poverty through conventional poverty statistics is challenging in view of their limited spatial resolution and focus on monetary indicators. In Indonesia, poverty measurement remains largely expenditure-based, potentially obscuring localized deprivations in education, health, and living standards. The objective of this present study is to address this limitation by developing a granular spatial mapping framework for the Multidimensional Poverty Index (MPI) in East Java Province. Employing the Alkire–Foster approach and Susenas 2023 data, the provincial MPI is estimated at 0.0479, and MPI values are spatially predicted at a 3 × 3 km grid resolution by integrating geospatial indicators of infrastructure accessibility, education and healthcare facilities, nighttime light intensity, and population density. The spatial models demonstrate strong predictive performance ($R^2 \approx 0.97$; AUC ≈ 0.98), revealing pronounced fine-scale variation in multidimensional poverty and identifying deprivation clusters that are not observable in administrative-level statistics. Areas characterized by geographic isolation and limited-service accessibility consistently exhibit elevated predicted MPI values. The findings of this study highlight the significance of high-resolution multidimensional poverty mapping in facilitating the development of more spatially targeted and evidence-based poverty reduction policies at the local level.

Keywords: Granular multidimensional poverty; machine learning; spatial mapping; random forest; East Java

1. Introduction

Poverty continues to represent a critical global challenge that necessitates a precise and policy-relevant measurement. Conventional poverty assessments, predominantly based on household income or expenditure surveys, demonstrate their persistent limitations in terms of high implementation costs, infrequent data collection, and coarse spatial resolution. These constraints then impede their capability to capture localized deprivation and to support targeted policy interventions, particularly in geographically diverse regions. In recent years, advances in machine learning (ML) and geospatial technologies have expanded the possibilities for poverty mapping through the integration of multi-source remote sensing and spatial data (Putri et al., 2022). Empirical studies demonstrate the efficacy of machine learning (ML) methods, including Random Forest, in revealing micro-geographical poverty patterns. In addition, nighttime light (NTL) data has emerged as a robust proxy for economic activity when combined with other spatial indicators (Li et al., 2019; Putri et al., 2023).

Despite these technological developments, many developing countries, including Indonesia, continue to rely primarily on unidimensional poverty measures. Statistics Indonesia (BPS), for instance, by tradition defines poverty based on consumption expenditure thresholds. While this approach provides a general overview of economic deprivation, it fails to capture non-monetary dimensions of poverty such as access to education, healthcare, housing quality, and basic services, that constitute integral components of community welfare (Sumargo et al., 2019). Consequently, poverty is frequently underestimated in areas where income or expenditure levels may be sufficient, yet access to essential services remains limited, particularly in rural and geographically isolated areas.

In response to these limitations, Chambers (1995) developed the multidimensional poverty framework integrating five interacting dimensions: material poverty, powerlessness, physical vulnerability, geographical isolation, and social vulnerability. This conceptual evolution is instrumental in the development of the Multidimensional Poverty Index (MPI) by Alkire and Foster (2011), a tool now widely adopted by various countries and international organizations. The MPI framework provides a more comprehensive assessment of poverty by incorporating multiple dimensions of deprivation. However, methodological challenges remain in operationalizing MPI within a spatially explicit framework. Traditional MPIs demonstrate limited scalability in capturing broad spatial disparities due to their dependence on census or household

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https://doi.org/10.21924/chss.5.2.2025.106

survey data (Zhou et al., 2022). Conversely, spatial poverty indices such as the Relative Spatial Poverty Index (RSPI) emphasize geographical characteristics but frequently lack a robust multidimensional poverty conceptualization (Putri et al., 2022).

This divergence reveals a critical methodological gap in poverty research: spatial approaches frequently lack conceptual depth in representing multidimensional deprivation, while multidimensional poverty measures frequently lack sufficient spatial granularity to inform localized interventions. Existing studies that incorporate spatial variables into MPI frameworks typically treat geographic characteristics, such as elevation, precipitation, or nighttime light intensity as individual indicators within the index, rather than integrating spatial information as a structural component of the poverty modeling process (Zhou et al., 2022).

East Java Province is an appropriate case study to address this gap due to its pronounced geographical and socio-economic heterogeneity. The province is characterized by geographical features, including densely urbanized metropolitan areas, remote rural and island regions. This diversity result in substantial disparities in infrastructure availability, service accessibility, and development outcomes across various administrative levels (Putri et al., 2022). These characteristics highlight the necessity for poverty measurement approaches that can simultaneously capture multidimensional deprivation and spatial variation at a finer resolution than conventional administrative units.

This study, building on the emphasis of geographical isolation as a key dimension of poverty (Chambers, 1995), proposes a spatially-based multidimensional poverty measurement approach integrating the Alkire–Foster MPI framework with machine learning and geospatial analysis. In contrast to previous studies that utilize spatial data merely as auxiliary indicators, this research treats spatial accessibility, infrastructure distribution, and geographic context as core predictive features for modeling and estimating MPI values at a granular grid level. By applying this approach to East Java, the study aims to generate high-resolution multidimensional poverty maps that reveal localized pockets of deprivation and provide stronger empirical support for spatially targeted and evidence-based poverty alleviation policies.

2. Methodology

This present study adopts a spatially explicit analytical framework to estimate and map multidimensional poverty at a granular scale. The methodology is comprised of two main components: (1) data collection and preparation, and (2) data analysis and modeling. This structure ensures a clear separation between data sources and analytical procedures, while maintaining a coherent workflow from MPI construction to grid-level spatial prediction.

2.1. Study area

East Java is one of 38 provinces in Indonesia with Surabaya as the capital province. This province consists of 38 regencies/municipalities. The percentage of East Java in poverty in 2023 reached 10.35, or approximately 4.19 million people living in poverty (BPS-Statistics Indonesia, 2023). Fig. 1 portrays the map of East Java as the case study, along with the distribution of official poverty data at the regency/municipality level in 2023.

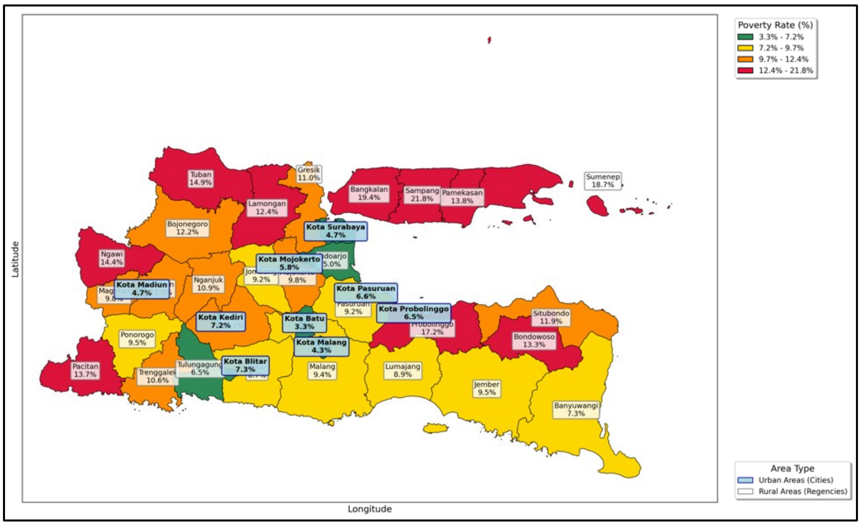

Fig. 1. East Java, Indonesia as the case study area and its poverty rate

As illustrated in Fig. 1, poverty in East Java is unevenly distributed across space, with higher poverty rates concentrated in Madura Island, the northern coastal areas, and the eastern “Tapal Kuda” region. Whereas major urban centers including Surabaya, Malang, and Batu report substantially lower poverty rates. This spatial pattern highlights pronounced regional disparities that are shaped by differences in infrastructure availability, accessibility to services, and proximity to urban economic centers.

2.2. Data collection and preparation

The multiple data sources were integrated to capture both multidimensional deprivation and spatial context. Firstly, household-level socioeconomic data were obtained from the March 2023 National Socioeconomic Survey (Susenas), Core

Module, conducted by Statistics Indonesia (BPS). These data provide information on education, health, housing conditions, and access to basic services, utilized to construct the Multidimensional Poverty Index (MPI) following the Alkire–Foster methodology.

Secondly, spatial data on public facilities were collected from OpenStreetMap (OSM). These include the locations of education facilities, healthcare facilities, and basic infrastructure such as electricity supply points, water facilities, and fuel stations. Facility data were employed to represent accessibility to essential services across geographic space.

Thirdly, nighttime light (NTL) data were sourced from the Visible Infrared Imaging Radiometer Suite (VIIRS) to capture spatial variation in economic activity. Concurrently, population density data were obtained from the WorldPop database to represent the spatial distribution of population. All spatial datasets were projected to a common coordinate reference system and harmonized to ensure spatial consistency.

2.3. Multidimensional poverty index (MPI) construction

The *Global Multidimensional Poverty Index Report* (2024) implicitly indicates that the UNDP and OPHI formulated the Multidimensional Poverty Index (MPI), encompassing three core dimensions: education, health and a decent standard of living (Alkire et al., 2023; Alkire, 2016; Alkire & Santos, 2013). Table 1 presents the dimensions and indicators of MPI utilized in this study. The selection of indicators was based on the data availability, and the weights used exerted the same value for each indicator.

Table 1. Dimensions and indicators used in MPI Measurements

Dimensions	Indicators (I_i)	Deprivation Threshold	Weights (w_i)	References
Education (1/3)	Mean Years Schooling	Less than 9 years of schooling for individuals aged 15+	1/9	UNDP, 2024
	School Attendance	Not attending school for children aged 5-17	1/9	UNDP, 2024
	Literacy	Unable to read and write for individuals aged 15+	1/9	Sumargo, B et al., 2019
Health (1/3)	Birth Assistance	Delivery not assisted by trained health personnel	1/9	Sumargo, B et al., 2019
	Health Insurance Access	Individuals without any form of health insurance	1/9	Artha, D. R. P., & Dartanto, T. (2018)
	Healthcare Access	Unable to access healthcare due to cost, distance, or quality issues	1/9	Chen, X et.al., 2022
Standard of Living (1/3)	Electricity Access	Households using non-PLN electricity or non-electric lighting	1/18	UNDP, 2024
	House Wall Materials	Walls made of wood/planks, bamboo weaving, wood logs, bamboo, or other poor materials	1/18	UNDP, 2024
	House Floor Materials	Floor made of wood/planks, bamboo, low quality wood/boards, soil and other materials	1/18	UNDP, 2024
	Cooking Fuel	Households using traditional fuels such as wood, charcoal, kerosene, briquettes, or other traditional fuels	1/18	UNDP, 2024
	Improved Water Access	Households using unimproved water sources such as unprotected well, unprotected spring, surface water, rainwater, or other poor sources	1/18	UNDP, 2024
	Assets Ownership	Households not owning any of: motorcycle, TV, AC, refrigerator, or car	1/18	UNDP, 2024

An individual is identified as multidimensionally poor if his deprivation score (c_i) is less than the poverty cutoff of 1/3 (0.333). This threshold is designed to ensure that poverty identification requires substantial deprivation across multiple dimensions.

$$c_i = w_1 I_1 + w_2 I_2 + \cdots + w_d I_d \tag{1}$$

where $I_i = 1$ (if someone is deprived in indicator i), $I_i = 0$ (if not deprived) and w_i is the weight of indicator i with $\Sigma_{i=1} w_i = 1$

$$H = \frac{q}{n} \tag{2}$$

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q} \tag{3}$$

$$MPI = H \times A \tag{4}$$

H (multidimensional poverty headcount) is proportion of the number of multidimensional poor people to the total population; A (multidimensional poverty intensity) refers to the weighted average proportion of indicators in which poor people are deprived; q is the number of individuals categorized as poor multidimensionally, n is the total population, k is the amount of deprivation that a person must experience to be categorized as poor, and $c_i(k)$ is the deprivation sensor score.

2.4. Spatial feature engineering

Spatial feature engineering was conducted to transform raw geospatial data into meaningful predictors for poverty estimation. For each grid cell, spatial features were derived to represent accessibility, infrastructure availability, and geographic context. The process involved the extraction of spatial features across multiple buffer zones to capture varying scales of spatial influence (Yeh et al., 2020). The accessibility features of the facility included counts and densities of education, healthcare, and infrastructure facilities within multiple buffer distances, as well as distances to the nearest facility of each type.

Urban accessibility was measured by the distances from each location to major urban centers in East Java, including Surabaya, Malang, Kediri, Jember, and Madiun, reflecting urban–rural gradients. These locations correspond to the officially designated urban service centers (PKN/PKW) in the East Java Provincial Spatial Plan (RTRW), as defined under Perda Jatim No. 10/2023. The socioeconomic spatial features included nighttime light intensity and population density. Furthermore, spatial lag variables were constructed using queen contiguity weights to account for neighborhood effects and spatial autocorrelation (Anselin, 2024), thereby capturing the influence of surrounding grid cells on local poverty outcomes. Comprehensive spatial feature set across multiple thematic categories is outlined in Table 2.

Table 2. Dimensions and indicators used in MPI Measurements

Categories	Features	Buffer Zone	Data Sources
Geographic Context	Raw coordinates	–	East Java Administrative Maps (Grid Centroid)
	Normalized coordinates [0, 1]	–	Derived
Infrastructure Accessibility	Education facility count	5, 10, 15 km	OpenStreetMap
	Education facility density	5, 10, 15 km	OpenStreetMap (Derived)
	Distance to nearest education facility	–	OpenStreetMap (Calculated)
	Healthcare facility count	5, 10, 15 km	OpenStreetMap
	Healthcare facility density	5, 10, 15 km	OpenStreetMap (Derived)
	Distance to nearest healthcare facility	–	OpenStreetMap (Calculated)
	Infrastructure facility (electricity, water supply, gas station) count	3, 5, 10 km	OpenStreetMap
	Infrastructure facility density	3, 5, 10 km	OpenStreetMap (Derived)
	Distance to nearest infrastructure	–	OpenStreetMap (Calculated)
Socioeconomic Indicators	Nighttime light (NTL) intensity	–	NOAA-VIIRS
	Population density	–	WorldPop Hub
Urban Accessibility	Distances to major cities (Surabaya, Malang, Kediri, Jember, Madiun)	–	East Java Administrative Maps (Calculated)
	Spatial Lag of Infrastructure Count	5, 10, 15 km	Queen Contiguity

2.5. Machine learning modeling

Machine learning techniques were applied to predict multidimensional poverty indicators at the grid level. Feature scaling was performed using ‘StandardScaler’ to normalize variables across different measurement units, ensuring optimal model performance (Pedregosa et al., 2011).

Random Forest regression was employed to estimate continuous MPI values and multidimensional poverty headcount ratios due to its robustness to non-linear relationships (Salman et al., 2024) and its ability to handle complex interactions among spatial features. The pipeline employed a stratified train-test split (80:20) to ensure representative sampling across poverty levels while preserving spatial structure.

For binary classification, the Logistic Regression model with balanced class weights was utilized for the purpose of classifying grid cells according to multidimensional poverty status. Regularization was applied to mitigate the risk of overfitting (James et al., 2021). The model training and evaluation processes were executed through an 80:20 train–test split, and model performance was assessed using standard regression and classification metrics, including the coefficient of determination (R^2), error measures, accuracy, and the area under the ROC curve (AUC). Hyperparameter tuning was performed to optimize regularization strength (C: 0.001-100), solver selection ('liblinear', 'lbfgs'), and maximum iterations (2000, 5000). Cross-validation procedures were utilized to ensure the generalizability of the model across spatial domains, with particular attention being paid to spatial autocorrelation effects that have the potential to inflate performance metrics (Roberts et al., 2017).

2.6. Grid-level prediction and mapping

The trained models were applied to all 3×3 km grid cells to generate spatially explicit predictions of multidimensional poverty indicators across East Java. Grid-level predictions facilitate the visualization of continuous poverty surfaces and the identification of localized pockets of deprivation that are not observable using administrative-level statistics.

Predicted MPI values and poverty classifications were mapped to produce high-resolution spatial representations of multidimensional poverty distribution. These maps offer a practical instrument for identifying priority areas for policy intervention and for supporting more spatially targeted and evidence-based poverty alleviation strategies.

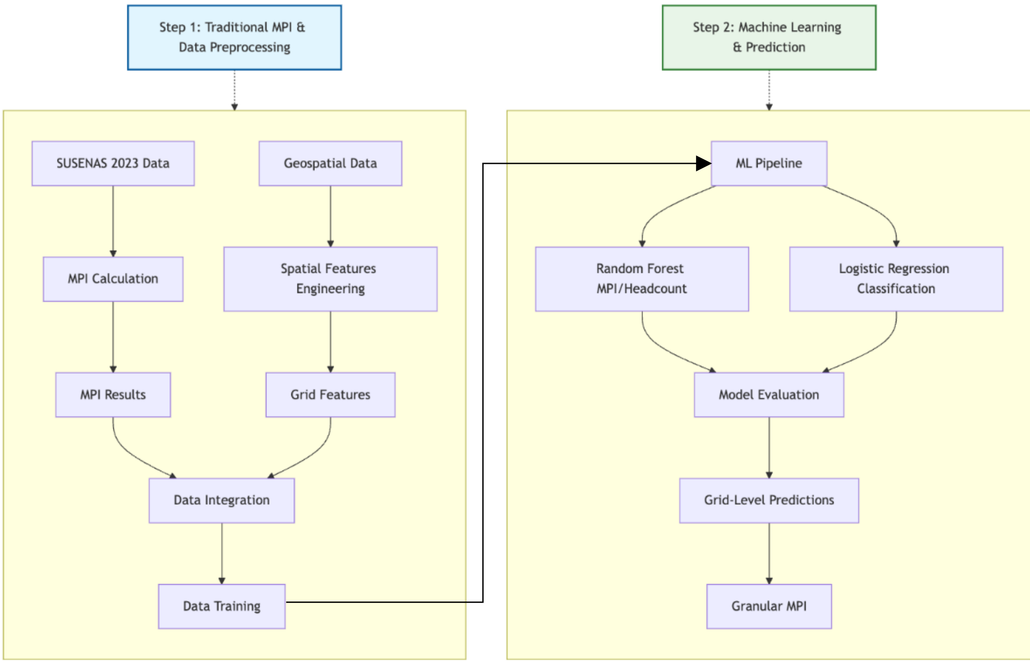

Fig. 2. The research framework of this study.

3. Results and Discussion

3.1. Multidimensional Poverty Index

The MPI analysis of East Java Province in 2023 provides a comprehensive picture of poverty that extends beyond traditional monetary measures, utilizing the Alkire-Foster methodology across 12 indicators spanning the domains of education, health, and living standards dimensions. The provincial MPI stands at 0.0479, with a headcount ratio of 12.67% (approximately 5.13 million people out of 40.49 million total population) and an intensity of 37.80%, indicating that multidimensionally poor individuals experience deprivation in more than one-third of the weighted indicators.

Table 3. MPI results of East Java, 2023

Poverty Measures	MPI (Multidimensional)	BPS (Monetary)
Methodology	Alkire-Foster approach with 12 indicators across 3 dimensions	Expenditure-based poverty line
Poverty Index	0.0479	–
Headcount Ratio	12.67%	10.35%
Poor Population	5.13 million people	4.19 million people
Intensity of Poverty	37.80%	–
Education Dimension	17.10%	–
Health Dimension	53.00%	–
Living Standards Dimension	29.90%	–

The close correspondence between the multidimensional headcount ratio (12.67%) and the official monetary poverty rate reported by BPS (10.35%) is consistent with previous findings that income-based poverty measures partially overlap with multidimensional deprivation (Alkire & Foster, 2011; Putri et al., 2022). However, the MPI framework has been demonstrated to reveal dimensions of deprivation that are not apparent in expenditure-based statistics, particularly in the domains of health and living standards. As demonstrated in other regional MPI studies, there is a lack of correlation between monetary sufficiency and adequate access to healthcare, housing quality, or basic services (Zhou et al., 2022). This reinforces the argument that the measurement of multidimensional poverty provides complementary insights to official monetary poverty statistics, rather than competing with them.

A breakdown by dimension reveals that the most significant contributor to overall deprivation comes from the health dimension, accounting for 53.00 percent of the total intensity. This finding suggests the presence of significant deficiencies in the accessibility of healthcare services. The dimension of living standards contributes 29.90 percent, reflecting challenges such as inadequate housing, lack of access to clean water, or limited access to basic utilities. Conversely, the education dimension contributes the least, at 17.10 percent, indicating relatively better outcomes in educational attainment when compared to the other dimensions.

The analysis of MPI at the regency and municipality-levels in East Java reveals substantial spatial heterogeneity in multidimensional poverty patterns across the 38 administrative units. The MPI values range from 0.0108 in Blitar Municipality to 0.0961 in Sumenep Regency, representing an 8.9-fold variation that significantly exceeds the provincial average of 0.0479. This pronounced spatial disparity indicates that multidimensional poverty is not uniformly distributed across the province, with distinct clustering patterns that reflect underlying socioeconomic and geographical factors.

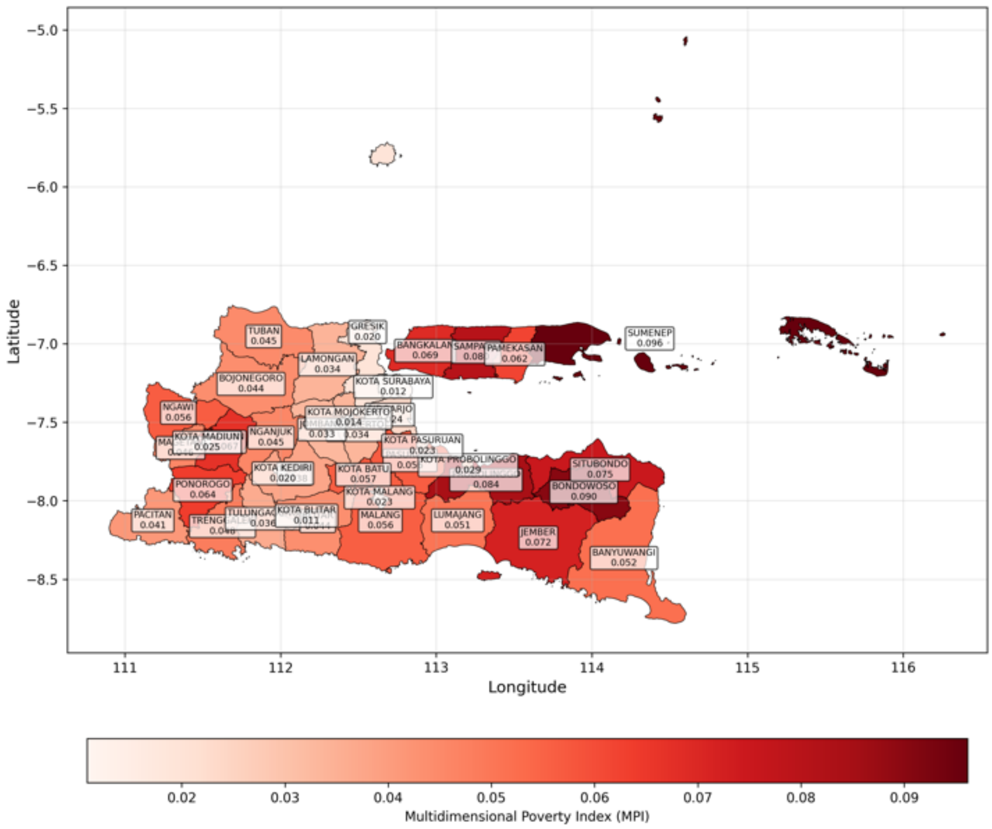

Fig. 3. MPI map by regency/municipality in East Java, 2023

Rural regencies demonstrate consistently higher MPI values compared to urban municipalities, with the ten highest-ranking areas being predominantly rural: Sumenep (0.0961), Bondowoso (0.0903), Probolinggo (0.0842), Sampang (0.0803), Situbondo (0.0752), Jember (0.0721), Bangkalan (0.0689), Madiun (0.0669), Ponorogo (0.0637), and Pamekasan (0.0620). Conversely, the eight lowest MPI values are recorded in urban areas, with Blitar Municipality (0.0108), Surabaya Municipality (0.0121), Mojokerto Municipality (0.0138), Gresik (0.0196), Kediri Municipality (0.0203), Malang Municipality (0.0227), Pasuruan Municipality (0.0233), and Sidoarjo (0.0236) all falling below the provincial average.

The eastern regencies, particularly those in the Madura Island and Tapal Kuda region, demonstrate the highest concentration of multidimensional poverty, suggesting that geographical isolation, inadequate infrastructure development, and constrained access to urban economic opportunities may contribute to persistent multidimensional deprivation in these areas (Zhou, Q et al, 2022).

The MPI patterns at the regency level observed in Fig. 3 are broadly consistent with earlier spatial poverty studies in East Java. These earlier studies identified Madura Island and the eastern Tapal Kuda region as structurally disadvantaged areas due to geographic isolation and limited infrastructure (Putri et al., 2022; Wahed et al., 2021).

Nevertheless, while administrative-level MPI mapping effectively highlights inter-regional disparities, it remains insufficient for identifying intra-regional heterogeneity, particularly within large rural regencies. This limitation motivates the necessity for a finer spatial resolution to capture localized deprivation patterns that are obscured by administrative aggregation.

3.2. Spatial Modeling for MPI Prediction

The spatial feature engineering process established a comprehensive 3×3 km grid system (total 5,868 grid cells) covering East Java province, generating 48 distinct variables that capture multidimensional aspects of spatial accessibility and infrastructure distribution. The grid-based approach facilitated fine-scale spatial analysis by incorporating healthcare facility access (faskes_count, faskes_density), infrastructure availability (infra_count, infra_density), educational facility distribution (edu_count, edu_density), nighttime light intensity as a proxy for economic activity, and population density metrics. Furthermore, spatial lag features were computed to capture neighborhood effects, while distance-based variables measured geographic isolation from key services. This methodological framework successfully transformed point-based facility data into spatially continuous variables suitable for machine learning applications, with each grid cell containing standardized measurements of local and neighboring infrastructure accessibility.

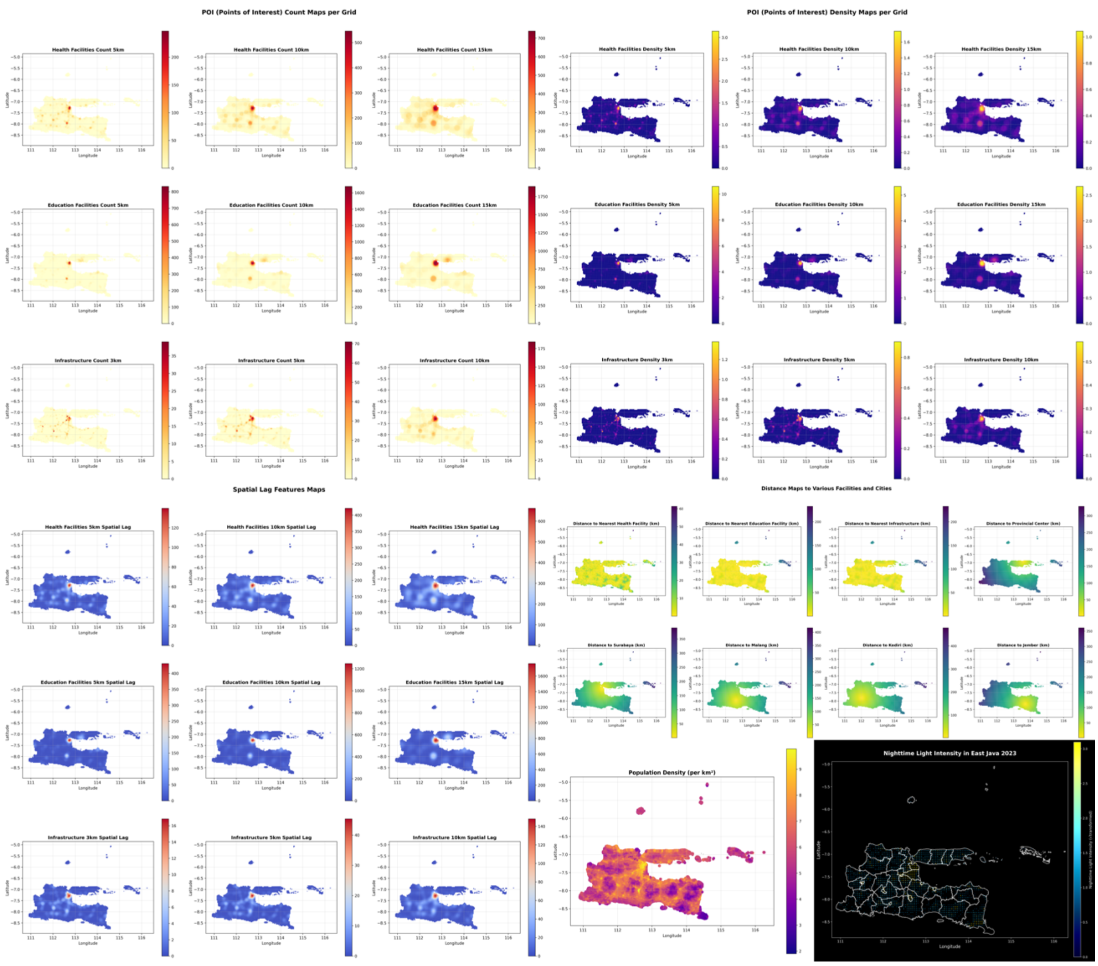

Fig. 4. Transformed data of spatial features used in this study

A comprehensive correlation analysis revealed systematic relationships between infrastructure accessibility and MPI. The findings of the study demonstrated that healthcare facility count with spatial lag effects (15km radius) exhibited the strongest negative correlation with MPI ($r = -0.398$, $p < 0.001$). This was followed by infrastructure count with spatial lag effects (10km radius) ($r = -0.386$, $p < 0.001$), and educational facility count with spatial lag effects (15km radius) ($r = -0.176$, $p < 0.001$). While these correlations vary in magnitude, they represent highly significant associations across 5,868 grid cells, indicating consistent patterns of infrastructure-poverty relationships. Conversely, distance-based features exhibited positive correlation with poverty measures, thereby confirming the hypothesis that geographic isolation is associated with the increased probability of multidimensional deprivation.

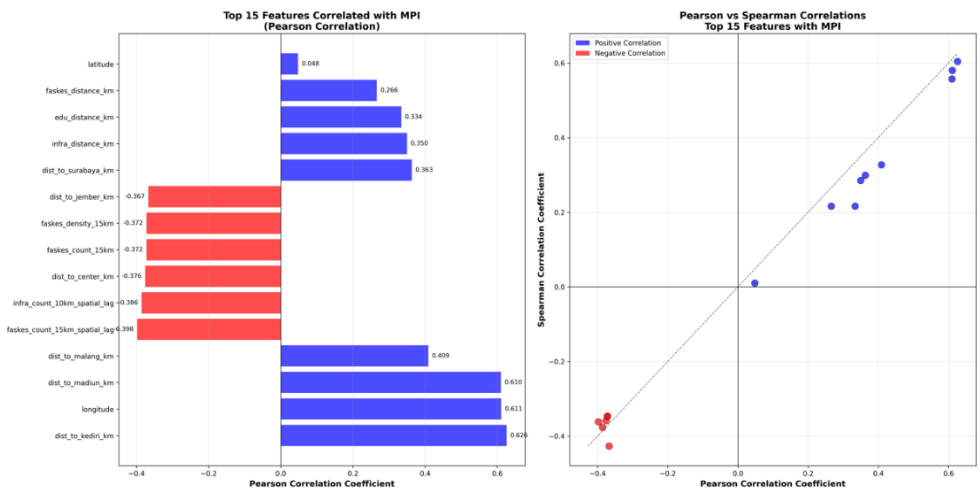

Fig. 5. Top 15 spatial features correlated with MPI (Pearson-Spearman correlation)

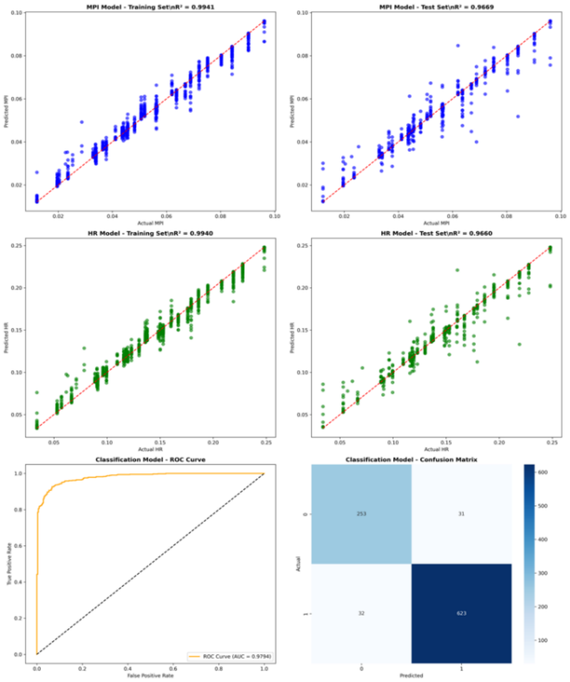

Fig. 6. Model performance analysis of Random Forest and Logistic Regression

The engineered features were systematically prepared for model training through standardization and validation procedures. This multidimensional spatial feature space was found to be an effective means of capturing the complex geographic relationships influencing MPI distribution. It was further found to enable the implementation of both regression and classification approaches to predict multidimensional poverty indicators with high precision.

Random Forest Regression

The Random Forest regression models demonstrated exceptional predictive capability across both poverty indicators. For MPI prediction, the model achieved an R^2 of 0.9669 on test data with remarkably low error metrics (MSE: 0.0000122, MAE: 0.00138). This finding indicates that the spatial features account for approximately 97% of the variance in multidimensional poverty. Similarly, the multidimensional headcount poverty model attained an R^2 of 0.9660 (MSE: 0.0000790, MAE: 0.00358), confirming robust performance across a range of poverty measures. The Random Forest algorithm's approach effectively captured non-linear relationships and feature interactions inherent in spatial poverty patterns.

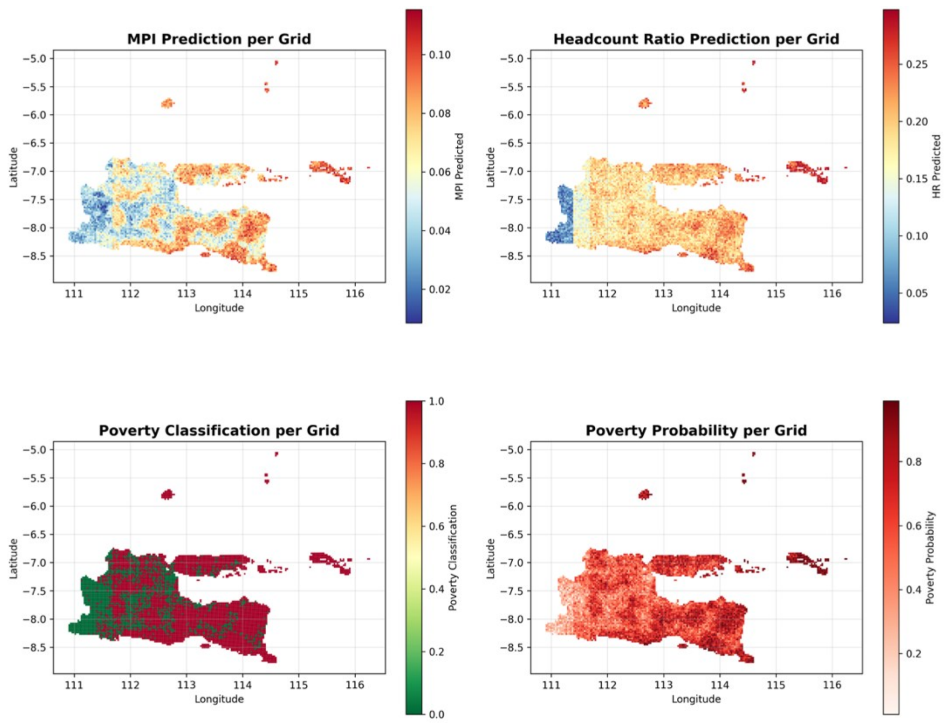

Fig. 7. 3×3 km grid mapping for granular MPI prediction and classification in East Java, 2023

Logistic Regression Classification

The logistic regression model for binary MPI classification demonstrated outstanding discriminatory performance with an AUC of 0.9794 and accuracy of 93.29% on test data. The metrics indicate excellent model calibration and the ability to distinguish between poor and non-poor grid cells with high precision. The model has learned that geographic isolation (measured by distance to key urban centers) is one of the strongest predictors of MPI in East Java. This finding suggests that spatial accessibility and proximity to economic hubs are critical factors in determining poverty levels at the grid cell level. Cross validation procedures were utilized to confirm the model stability and generalizability across various spatial subsets of the data.

3.3. Grid-based mapping results for granular MPI

The grid-based MPI mapping at a 3×3 km resolution represents a significant methodological advancement over conventional administrative-level poverty analysis. While previous studies have primarily reported poverty patterns at the level of the regency or the municipality, the grid-based approach reveals substantial micro-spatial heterogeneity within administrative units. This study demonstrates that areas officially classified as low-poverty regions may still contain concentrated pockets of multidimensional deprivation, thus highlighting the limitations of aggregated statistics for policy targeting. The mapping results identified specific geographic hotspots of multidimensional poverty grids, particularly in mountainous regions, coastal areas with limited infrastructure, and peripheral districts distant from major urban centers.

a. **Tapal Kuda Region (Eastern Horseshoe):** The eastern border regions demonstrate elevated level of poverty, with Situbondo leading at 91.01% poor grids (MPI range: 0.036-0.115, mean: 0.078), followed by Banyuwangi at 90.27% poor grids (MPI range: 0.039-0.115, mean: 0.079), and Bondowoso at 88.24% poor grids (MPI range: 0.026-0.111, mean: 0.076). This horseshoe-shaped pattern reflects persistent geographic isolation from major urban centers, where mountainous terrain and peripheral border positions limit economic integration with Java's core urban corridor. These findings are consistent with those of previous studies indicating that economic growth in disadvantaged eastern regions of East Java lags behind surrounding areas (Wahed et al., 2021). However, the grid-based MPI mapping extends earlier analyses by revealing that multidimensional deprivation is spatially concentrated within specific mountainous and peripheral corridors rather than being uniformly distributed across regencies. This fine-scale spatial insight provides actionable information for targeting infrastructure development and social service expansion in areas where geographic isolation most strongly amplifies multidimensional poverty.

b. **Madura Island:** All four Madura regencies exhibit high coverage of poor grids: Sumenep (94.97%), Sampang (87.08%), Pamekasan (78.57%), and Bangkalan (86.79%). This island-wide pattern demonstrates how geographic isolation compounds poverty, despite Bangkalan's proximity to Surabaya via the Suramadu Bridge. The consistently high MPI values (0.064-0.087) across Madura reflect limited infrastructure development and economic opportunities when compared to mainland Java. This phenomenon is particularly evident in coastal communities on Madura Island, where economic vulnerability is significantly determined by poor infrastructure, limited market access, and a lack of modern technology (Riniwati et al., 2023). The findings indicate that multidimensional poverty is not exclusively driven by island-wide isolation, rather, but is further influenced by local disparities in infrastructure accessibility and service provision. This level of spatial detail enables policymakers to differentiate between structurally disadvantaged coastal communities and relatively better-connected areas, thus supporting the development of more differentiated and effective poverty alleviation strategies within the island.

c. **Coastal Areas:** Coastal regions in East Java demonstrate a heterogeneity of multidimensional poverty patterns. Northern coastal regencies such as Tuban (65.57%) and Lamongan (67.13%) demonstrate moderate poverty levels, benefiting from industrial development and stronger economic interconnectivity with Surabaya. In contrast, southern and eastern coastal areas, including Lumajang (85.97%) and Situbondo (91.01%), experience substantially higher poverty prevalence. These disparities indicate that coastal proximity alone does not guarantee improved welfare outcomes. As noted by Hendarto (2019), developmental trajectories in East Java's coastal regions are shaped by factors such as infrastructure availability and historical economic integration rather than geographic position. The Pantura (northern coast) has benefited from enhanced connectivity to the Javanese economic corridor, while the Pansela (southern coast) exhibits lagging indicators due to inadequate infrastructure and limited integration. The grid-based MPI mapping reinforces this distinction by revealing that multidimensional poverty in coastal areas is more strongly associated with infrastructure quality and economic connectivity than with proximity to the coastline itself. This finding highlights the significance of fine-scale spatial analysis in informing differentiated coastal development strategies rather than uniform, location-based policy approaches.

d. **Mountainous Areas:** Mountainous regions in the southern part of the regencies exhibit varied patterns. Pacitan (1.06%) exerts the lowest coverage of poor grids, while Trenggalek (49.46%) and Ponorogo (24.32%) demonstrate moderate levels. This variation suggests that the impact of mountainous terrain is dependent upon accessibility to urban markets and infrastructure development. In Pacitan, though predominantly characterized by highland terrain, the exceptionally low poverty coverage reflects the enhanced accessibility and the potential for tourism development near urban centers, as highlighted by Putri & Susilowati (2018). By contrast, Trenggalek and Ponorogo face recurrent road disruptions and landslide risk, which undermine access to markets and public services, locking in moderate poverty grids as shown in landslide susceptibility studies by Banuzaki et al. (2022). The grid-based MPI mapping highlights how localized accessibility constraints within mountainous regions translate into concentrated pockets of multidimensional deprivation, thereby underscoring the importance of integrating topographic risk and infrastructure resilience into spatial poverty analysis and regional planning.

e. **Urban Proximity Effects**: Regencies surrounding major cities show clear distance decay effects. The regions near Surabaya (i.e. Sidoarjo: 46.99% and Gresik: 72.52%) have lower poverty in comparison to more distant regions. Malang's surroundings show moderate poverty (Malang: 78.00%), while Kediri's vicinity demonstrates strong urban influence (Kediri: 49.38%, and Kota Kediri: 15.79%). The analysis of grid-level MPI captures these spatial gradients with greater precision than statistics at the administrative level. This demonstrates how proximity to urban centers can shape multidimensional welfare outcomes at a fine spatial scale. This finding reinforces the relevance of spatially targeted development strategies that leverage urban–rural linkages while addressing localized accessibility gaps.

The apparent discrepancy between the high proportion of poor grids identified in this study (67.43%) and the lower poverty rates reported by the conventional MPI (12.67%) and the official monetary measure (10.35%) is indicative of fundamental methodological differences rather than empirical inconsistency. The grid-based MPI classification is a comprehensive measure of multidimensional deprivation across education, health, and living standards, whereas monetary poverty measures are confined to income or expenditure thresholds. As a result, a grid cell may be classified as poor (MPI > 0.033) even when most of its residents are not income-poor.

This distinction is particularly evident in rural areas where the presence of basic income sufficiency may coexist with limited access to quality education, healthcare, and infrastructure. By employing a 3×3 km spatial resolution, the proposed approach captures micro-level deprivation patterns that are obscured by administrative-level aggregation. Conventional poverty statistics are calculated by averaging conditions across entire regencies, thereby smoothing over localized pockets of deprivation. In contrast, the grid-based analysis reveals that significant multidimensional poverty can persist within regions that are officially classified as non-poor.

Policy Implications

The findings demonstrate that 3×3 km grid-based MPI mapping noticeably enhances policy targeting accuracy when compared to conventional administrative-level poverty statistics. The identification of localized pockets of multidimensional deprivation enables policymakers to design geographically targeted interventions that prioritize specific communities rather than uniformly allocating resources across entire regencies.

In terms of infrastructure planning, the integration of MPI with spatial accessibility indicators facilitates the identification of areas where poor health and living standards coincide with limited access to facilities. This information can guide the placement of healthcare centers, educational facilities, and transportation infrastructure, particularly in rural, coastal, and island regions where service gaps are most pronounced. From a regional development perspective, the utilization of granular MPI mapping facilitates the implementation of differentiated development strategies that recognize spatial heterogeneity within administrative boundaries. This approach has been demonstrated to reduce the risk of policy mistargeting and enhance the effectiveness of poverty reduction programs by aligning interventions with local deprivation profiles.

Limitations and Future Possible Directions

The research on multidimensional poverty mapping in East Java faces several significant limitations to be considered when interpreting the results. The study's reliance on cross-sectional Susenas 2023 data provides only a snapshot of poverty at a single point in time, limiting analysis of poverty dynamics or trends. Furthermore, the dataset of 5,868 samples may not fully capture heterogeneity across all micro-geographic areas.

The technical limitations of the system include potential overfitting as evidenced by the substantial difference between the training R^2 (0.994) and the test R^2 (0.967), dependency on spatial autocorrelation that may create prediction issues, and an adaptive threshold method (67.43% poverty rate) that may not accurately reflect local conditions in areas with different poverty distributions. Data quality constraints involve the 3x3 km grid resolution potentially missing micro-level poverty pockets, dependency on current facility location data that may become outdated, and reliance on nighttime light data that may not capture informal economic activities or areas with irregular electricity access.

It is recommended that future research in multidimensional poverty mapping should prioritize the integration of longitudinal datasets to capture temporal dynamics and poverty transitions. This can be attained by moving beyond the current limitations of cross-sectional studies through te utilization of spatio-temporal modeling frameworks that are able to track changes over time. The enhanced model validation approaches, including robust cross-validation techniques and Bayesian methodologies, are deemed essential to address overfitting concerns and enhance generalizability across different geographic contexts (Jean et al., 2016; Steele et al., 2017). The incorporation of disparate data sources, particularly high-resolution satellite imagery, mobile phone data, and real-time environmental indicators, offers promising avenues for improving data quality and spatial resolution while addressing currency issues in facility mapping (Blumenstock et al., 2015; Chi et al., 2022). Methodological advances should focus on developing hierarchical modeling approaches that combine feature-based and image-based models, enabling multi-scale analysis from household to regional levels (Head et al., 2017; Yeh et al., 2020). To enhance interpretability and policy relevance, it is recommended that future studies should explore the potential of explainable AI techniques and conduct comparative validation studies that examine the relationship between multidimensional and monetary poverty measures across different contexts (Molnar, 2020; Zhao et al., 2019).

4. Conclusions

The spatial analysis of multidimensional poverty in East Java provides robust empirical support for the distance decay hypothesis, thereby demonstrating that geographic accessibility plays a critical role in shaping welfare outcomes. Remote and peripheral areas consistently exhibit higher MPI values, reflecting how geographic isolation compounds deprivation through limited access to essential services, infrastructure, and economic opportunities. Conversely, proximity to major urban centers such as Surabaya, Malang, and Kediri is associated with substantially lower multidimensional poverty, highlighting the significance of urban connectivity and spatial spillover effects.

The utilization of a 3×3 km grid-based framework has been demonstrated to be particularly effective in capturing fine-scale spatial heterogeneity obscured by administrative-level poverty statistics. The present study demonstrates that geographic context is not merely a backdrop for poverty but an active determinant that structures access to human development opportunities. This is demonstrated by the revelation of localized pockets of multidimensional deprivation within officially low-poverty regions. These findings contribute to the literature on spatial poverty by empirically linking multidimensional deprivation to spatial accessibility at a granular scale.

Nevertheless, several limitations should be acknowledged. The reliance on cross-sectional Susenas 2023 data has restricted the analysis to a single time point, thereby preventing the examination of poverty dynamics and transitions over time. Furthermore, despite the machine learning models exhibiting robust predictive performance, the potential for overfitting and reliance on spatial autocorrelation necessitate careful interpretation of the findings. It is recommended that future research should focus on developing spatio-temporal poverty models that integrate longitudinal data to capture changes in multidimensional deprivation over time. The utilization of higher-resolution geospatial data and complementary data sources could further enhance spatial precision and robustness. The advancement of these directions will serve to strengthen the role of spatially explicit multidimensional poverty measurement as a practical tool for evidence-based policy design and targeted poverty alleviation strategies.

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