Volume 4, No. 1 January 2026
p-ISSN 3032-3037 | e-ISSN 3031-5786

ADVANCES IN SOCIAL HUMANITIES RESEARCH

Development of Hierarchical Bayesian Statistical Model For Prediction of Multidimensional Poverty Patterns: Application of Spatial-Temporal Analysis to Disadvantaged Village Data in Eastern Indonesia

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Abstract
Multidimensional poverty in Eastern Indonesia is still a serious problem that is not only influenced by economic factors, but also by educational, health, infrastructure, and complex spatial conditions. Disadvantaged villages in the region face high development inequality, while the approaches to poverty measurement and prediction used so far are still conventional and less adaptive to spatial and temporal variations. This study aims to develop a Hierarchical Bayesian statistical model based on spatial-temporal analysis to predict multidimensional poverty patterns more accurately and contextually. The method used was a quantitative approach with spatial-temporal hierarchical Bayesian modeling, using multivariate panel data from 450 disadvantaged villages in East Nusa Tenggara, Maluku, and West Papua during the period 2015–2022. The model was analyzed using Markov Chain Monte Carlo (MCMC) and Integrated Nested Laplace Approximation (INLA) techniques for parameter estimation and risk prediction. The results show that the model is able to map poverty risk clusters spatially with high accuracy and capture significant temporal dynamics, especially during the pandemic. The largest contribution comes from indicators of sanitation and access to clean water. This model generates predictive risk and trend maps that can be used to support microdata-based development policies, as well as strengthen the accuracy of interventions in high-risk villages more effectively.

Keywords: multidimensional poverty, hierarchical bayesian, spatial-temporal analysis, disadvantaged villages, risk prediction

Introduction

Poverty in Indonesia is not only monodimensional such as limited income, but also includes the dimensions of health, education, access to infrastructure, and complex socio-economic conditions. In Eastern Indonesia, especially in disadvantaged villages, poverty has unique spatial and temporal characteristics and is different from other regions (Sumarto et al., 2020; Kurniawan & Dewi, 2021; World Bank, 2022). Therefore, modeling that is able to capture poverty dynamics in a multidimensional, space, and time manner is an important need to support more accurate and targeted policies.

Poverty alleviation policies in Indonesia are still dominated by a one-dimensional approach that does not take into account spatial and temporal variations between regions (Baş & Kirişci, 2026; Dou et al., 2022; Firdausy & Budisetyowati, 2022; Putri et al., 2023). This approach often results in ineffective policies, especially in disadvantaged village areas that have different geographical and social conditions (Suryahadi et al., 2019; Ananta et al., 2020; Pratomo & Kuncoro, 2021). Given the high inequality between regions, more flexible and contextual statistical approaches such as hierarchical Bayesian models are urgently needed to capture complexity and uncertainty in multidimensional poverty data.

Hierarchical Bayesian models allow for the integration of information at different levels—individuals, households, and administrative regions—and are able to address spatial and temporal dependency structures simultaneously (Banerjee et al., 2014; Gelman et al., 2013; Cressie & Wikle, 2011). In the context of multidimensional poverty, this model can be used to predict important indicators such as access to clean water, education, health services, and asset ownership by taking into account geographical patterns and time trends.

Table 1. Multidimensional Poverty Indicators in Disadvantaged Villages (Eastern Indonesia)

Indicator	Average (%)	Standard Deviation	Data Year
Access to clean water	46.3	12.4	2021
School dropouts (ages 7–15)	18.7	7.1	2021
Lack of proper sanitation	55.9	15.2	2021
Lack of electricity	29.5	10.3	2021

Source: BPS (2022), Ministry of Rural Development (2022), Satellite Data of Disadvantaged Villages (2021)

A number of studies have examined multidimensional poverty using statistical and spatial approaches (Permanyer, 2018; Alkire et al., 2021). Alkire & Santos (2014) developed the MPI (Multidimensional Poverty Index) which is used globally to measure poverty from various dimensions. In Indonesia, Badaruddin et al. (2020) examined poverty with a spatial approach in the Papua region, while Surbakti & Hadi (2019) used panel regression to analyze the determinants of poverty in disadvantaged areas (Wardhana et al., 2022; Pratama & Sari, 2021). However, most of those studies have not combined spatial and temporal dimensions simultaneously within a robust inferential statistical framework (Fischer & Wang, 2019).

Most previous approaches used static or cross-sectional analysis, which did not adequately represent the dynamics of time in the phenomenon of poverty (Ananta et al., 2020; Pratomo & Kuncoro, 2021; Surbakti & Hadi, 2019). In addition, the approach used has not taken into account the spatial correlation between adjacent villages, when in reality, poverty is often spread in geographically connected patterns (Banerjee et al., 2014; Cressie & Wikle, 2011; Rajaratnam et al., 2010). Thus, there is a methodological gap to develop a more realistic and robust prediction model.

This research offers a new approach in modeling multidimensional poverty in disadvantaged areas by developing a hierarchical Bayesian statistical model based on spatial-temporal analysis. This model will integrate spatial information between regions and time-series data from disadvantaged villages during the period 2015–2022, which was rarely done in previous studies in Indonesia (Gelman et al., 2013; Badaruddin et al., 2020; Kurniawan & Dewi, 2021). The advantage of this approach lies in its ability to capture data heterogeneity and hierarchical structures between regional levels simultaneously.

This research aims to develop a multidimensional poverty predictive model using a hierarchical Bayesian approach that is capable of capturing spatial and temporal variations simultaneously. The model is expected to improve the accuracy of poverty pattern predictions in disadvantaged villages in Eastern Indonesia and support more precise and contextually grounded data-driven policy formulation. Practically, this research aims to produce a multidimensional poverty risk map that can be utilized by local governments and relevant ministries to design more targeted and effective development interventions, while academically contributing to the expansion of Bayesian statistical methods for spatial-temporal applications in the socio-economic field and strengthening the integration of macro and micro data in poverty modeling. This study focuses on disadvantaged villages in Eastern Indonesia, specifically in the provinces of East Nusa Tenggara, Maluku, and West Papua, using data from the last eight years (2015–2022) with the village as the primary unit of analysis, which is linked spatially through coordinate mapping and temporally based on the year of observation, and the model is developed within the Markov Chain Monte Carlo framework with posterior estimation applied to each poverty indicator.

Method

This research uses a quantitative approach with a statistical modeling method based on Bayesian hierarchical modeling combined with spatial-temporal analysis. The aim of this approach is to develop a multidimensional poverty predictive model that takes into account interregional (spatial) variation and temporal dynamics, as well as accommodates stratified data structures such as individuals, households, and administrative regions (villages and sub-districts). The choice of this method is based on the complexity of the phenomenon of multidimensional poverty, which cannot be accurately explained through traditional linear models, especially when there is a geographical correlation between units of analysis and structural variations that occur over time.

The population in this study is all villages that are categorized as disadvantaged villages based on data from the Ministry of Villages, Development of Disadvantaged Regions, and Transmigration (Kemendes PDTT) in Eastern Indonesia, covering the provinces of East Nusa Tenggara, Maluku, and West Papua. Samples were taken using the purposive sampling method based on the availability of longitudinal data and the suitability of the multidimensional poverty indicators needed in the model. A total of 450 villages from the three provinces were selected as analysis units with data coverage during the 2015–2022 period. Each village is associated with geographic coordinates to support spatial modeling, and is classified based on indicators of education, health, housing, infrastructure access, and economic adequacy.

The main instrument in this study is a multivariate panel data set sourced from the Central Statistics Agency (BPS), the Ministry of Rural Development and Development, and spatial-based village information systems such as Village Satellites. The variables used include five main dimensions of multidimensional poverty: health (access to services, stunting prevalence), education (length of schooling, school dropout rate), living conditions (sanitation, electricity, clean water), access to the economy (decent work, asset ownership), and basic infrastructure (road access and transportation). To support spatial-temporal modeling, village geolocation data and administrative boundaries are used as a basis for constructing a spatial correlation matrix (adjacency matrix). This data is then combined in a hierarchical data framework to be analyzed using R software with INLA and WinBUGS libraries.

Data collection is carried out through the integration of secondary data from various government agencies that have been verified, including data from Susenas, Podes, and data on disadvantaged villages from the Ministry of Agriculture and Rural Development. In addition, spatial data is obtained from village coordinate maps and geospatial information based on GIS (Geographic Information System). The data collection process also includes the stage of cleaning and standardizing the indicators between years so that they can be used in longitudinal models. Initial validation is performed by matching the recap results of the aggregate data with the available microdata to ensure the consistency and integrity of the dataset.

The research procedure began with the preparation of a conceptual framework and mapping of multidimensional poverty indicators in accordance with the Alkire-Foster framework that has been adapted to the local context of Indonesia. After that, a hierarchical data structure was constructed, where the first level includes household/village indicators, the second level is sub-district/district, and the third level is province. The hierarchical Bayesian model was then constructed using the MCMC (Markov Chain Monte Carlo) approach to obtain the posterior parameter estimation of each indicator and predict the risk of multidimensional poverty in the spatial unit (village). This model is evaluated through posterior predictive checking and deviance information criterion (DIC) measurements to assess the suitability of the model.

The data analysis technique was carried out using Bayesian hierarchical spatial-temporal modeling which consists of three main components: fixed effects, spatial random effects, and temporal random effects. The analysis was carried out using the Bayesian inference approach using the MCMC sampling method and integrated nested Laplace approximation (INLA) for computational efficiency. In addition, a posterior uncertainty analysis and mapping of the estimated results were carried out in the form of a spatial-based multidimensional poverty risk map. The results of the model are visualized in the form of thematic maps with a scale per village, and accompanied by temporal trend graphs for each province to illustrate the dynamics of poverty change over time. The evaluation of model performance was carried out based on the prediction accuracy, reliability of parameter estimation, and spatial-temporal coherence of the resulting poverty pattern.

Results and Discussion

Data Description and Distribution of Multidimensional Poverty Indicators

Initial analysis was carried out on 450 disadvantaged villages in East Nusa Tenggara, Maluku, and West Papua using longitudinal data for the 2015–2022 period. The results of the exploration showed that poverty indicators such as access to clean water, school dropout rates, and decent sanitation ownership have high disparities between regions. The average access to clean water only reaches 46.3%, and there are still villages that do not have proper sanitation facilities (Kemendes PDTT, 2022; BPS, 2022; Alkire & Santos, 2014).

Spatially, it can be seen that the inequality of the distribution of indicators occurs consistently in remote coastal areas and hilly areas, which have limited access to infrastructure and basic services. Villages in West Papua show the highest prevalence of multidimensional poverty compared to the other two provinces (Surbakti & Hadi, 2019; Kurniawan & Dewi, 2021; Ananta et al., 2020). This is reinforced by qualitative data from village reports that show limited supply of water, electricity, and educational facilities.

The temporal pattern also shows an improvement trend in several indicators, such as an increase in electricity ownership and a decrease in school dropouts, but these improvements are uneven across regions. Villages in the red zone of multidimensional poverty tend to remain stagnant for the past eight years (Badaruddin et al., 2020; World Bank, 2022; Rajaratnam et al., 2010).

Table 2. Summary of Multidimensional Poverty Indicators (2015–2022)

Indicator	Red (%)	Std. Dev	Min (%)	Max (%)
Access to clean water	46.3	12.4	21.0	82.0
School dropout (ages 7–15)	18.7	7.1	5.3	39.5
Inadequate sanitation	55.9	15.2	27.0	90.2
Lack of electricity	29.5	10.3	8.7	62.0

Source: BPS & Ministry of Agriculture and Rural Development Secondary Data, 2023

The distribution of data shows that the indicators are correlated with each other and form geographically consistent poverty clusters. The spatial correlation between adjacent villages reinforces the importance of spatial approaches in modeling poverty, as they cannot be treated as independent units (Cressie & Wikle, 2011; Banerjee et al., 2014; Gelman et al., 2013).

In addition, variability between years illustrates that time dynamics have an important role in explaining poverty fluctuations, especially due to government program interventions and natural disasters that occur in several regions (Suryahadi et al., 2019; Pratomo & Kuncoro, 2021; Ananta et al., 2020).

With the results of this data exploration, it can be concluded that a spatial-temporal approach based on hierarchical statistics is a relevant methodology and is needed to overcome the challenges in mapping and predicting multidimensional poverty more accurately.

Spatial-Temporal Hierarchical Bayesian Model Estimation Results

A hierarchical Bayesian model was developed with three main components: fixed effects (poverty indicators), spatial random effects between villages, and temporal random effects between years. The estimation process was carried out using the MCMC approach and model validation through the Deviance Information Criterion (DIC). The resulting model shows stable convergence and high prediction performance (Gelman et al., 2013; Banerjee et al., 2014; Cressie & Wikle, 2011).

Fixed effects show that indicators of sanitation and access to clean water have the greatest contribution to the probability of multidimensional poverty. Meanwhile, the variables of education and electricity access tend to have a lower influence on average but are significant in certain regions (Alkire & Santos, 2014; Badaruddin et al., 2020; Rajaratnam et al., 2010).

The spatial effect shows the clustering of poverty between adjacent villages, especially in inland and coastal areas with minimal access to transportation. This confirms that villages cannot be analyzed independently, and the need for a spatial approach that considers geographical interconnections (Cressie & Wikle, 2011; Banerjee et al., 2014; Kurniawan & Dewi, 2021).

From a temporal perspective, the model shows that there was a fairly high fluctuation in poverty risk between 2017–2020, especially due to the impact of natural disasters and the COVID-19 pandemic. After 2021, there was a moderate improvement in some areas due to infrastructure development interventions and social assistance programs (Suryahadi et al., 2019; Pratomo & Kuncoro, 2021; World Bank, 2022).

These results reinforce the argument that hierarchical Bayesian models are not only able to capture variation between regions, but also effectively represent time dynamics, making them superior to conventional statistical approaches.

Model validation showed a DIC value of 4321.5, which indicates an excellent model fit compared to non-spatial-temporal models. In addition, the coverage interval value in the prediction reached 94%, proving the reliability of the estimation and generalization of the model in the village unit.

Visualization of Multidimensional Poverty Risk Map (Spatial Output)

The results of hierarchical Bayesian modeling were then visualized in the form of a multidimensional poverty risk map based on posterior predictions at the village level. This visualization illustrates the high or low probability of a village being in the multidimensional poverty category, based on the indicators used. The mapping was carried out using R and QGIS-based GIS software, and produced village-resolution spatial outputs that were informative for policy makers (Cressie & Wikle, 2011; Rajaratnam et al., 2010; Badaruddin et al., 2020).

The map shows that areas at high risk of multidimensional poverty (marked in dark red) are concentrated in the southern West Papua region, small islands in Southeast Maluku, and highlands in East Nusa Tenggara. All three have a common pattern in the form of geographical isolation, limited access to infrastructure, and uneven distribution of government assistance (Ananta et al., 2020; Kurniawan & Dewi, 2021; Ministry of Agriculture and Rural Development (PDTT), 2022).

On the other hand, there are also zones that show a consistent reduction in risk, especially in villages that are close to the district center and national road access. This emphasizes the importance of geographical factors in development policy interventions (Surbakti & Hadi, 2019; Gelman et al., 2013; World Bank, 2022).

This mapping also allows the identification of priority clusters of interventions, where high-risk villages that are close to each other can be used as strategic zones for the implementation of region-based development programs (Banerjee et al., 2014; Cressie & Wikle, 2011; Suryahadi et al., 2019).

In addition, local governments can use these outputs to allocate resources more efficiently, not only based on administrative categories, but also based on evidence-based and spatial risk predictions (Alkire & Santos, 2014; Pratomo & Kuncoro, 2021; BPS, 2022).

Overall, this spatial visualization demonstrates the power of the Bayesian approach in generating adaptive, precise, and structure-based risk maps that reflect the realities on the ground.

In addition to spatial output, the model also produces temporal estimates of multidimensional poverty risk from 2015 to 2022. The results show that there are differences in patterns of change between provinces, even between districts within one province. In general, the risk of poverty decreased moderately until 2019, then increased sharply in 2020 due to the COVID-19 pandemic (Suryahadi et al., 2019; World Bank, 2022; Pratomo & Kuncoro, 2021).

Table 3. Temporal Risk Trend of Multidimensional Poverty (2015–2022)

Year	Mean Risk Score	Std. Dev	Note
2015	0.612	0.104	Initial observation
2017	0.571	0.093	Mild drop
2019	0.538	0.086	Lowest risk point
2020	0.602	0.098	Surge due to the pandemic
2022	0.549	0.089	Post-pandemic recovery

Source: Bayesian Model Output, 2023

The surge in 2020 occurred significantly in the Papua and Maluku regions, where the distribution of social assistance was hampered by geographical conditions and restrictions on community activities. The limitations of digital connectivity also slow down the distribution of integrated data-based assistance (Kurniawan & Dewi, 2021; Surbakti & Hadi, 2019; World Bank, 2022).

Although 2022 showed a recovery trend, the risk value has not returned to its pre-pandemic lows. This shows that the impact of the pandemic is structural and requires a longer recovery time, especially in disadvantaged village areas (Gelman et al., 2013; Badaruddin et al., 2020; Cressie & Wikle, 2011).

This temporal trend also reveals that several districts have successfully taken advantage of the momentum of post-pandemic intervention to accelerate the development of basic infrastructure and educational services. This can be seen from the decrease in school dropout indicators and the increase in household asset ownership in several villages (BPS, 2022; Ministry of Agriculture and Rural Development (PDTT), 2022; Alkire & Santos, 2014).

By understanding these temporal dynamics, poverty alleviation policies need to be designed in layers—not only based on spatial conditions, but also considering intervention time, program sustainability, and post-disruption adaptation.

Policy Implications and Academic Contributions

The prediction model developed in this study offers a new approach to multidimensional poverty analysis in Indonesia, especially for disadvantaged areas that have not received granular data-based attention so far. The integration between spatial and temporal components in a hierarchical Bayesian model results in information that is not only descriptive, but also predictive and strategic (Banerjee et al., 2014; Cressie & Wikle, 2011; Gelman et al., 2013).

Model outputs such as risk maps and temporal trends provide an objective basis for evidence-based policy formulation, both at the national and local scales. Local governments can use these results to prioritize village development and budget allocation based on risk zones, not just based on administrative indicators (Pratomo & Kuncoro, 2021; World Bank, 2022; BPS, 2022).

For policymakers, one of the biggest benefits of this model is the ability to simulate scenarios—for example, the impact if certain infrastructure is upgraded on high-risk villages. This approach supports program planning that is more dynamic and adaptive to changing conditions (Suryahadi et al., 2019; Alkire & Santos, 2014; Ministry of Agriculture and Rural Development (PDTT), 2022).

The academic contribution of this research lies in the application of the spatial-temporal Bayesian model in the study of multidimensional poverty at the micro (village) level, which is still very rarely done in Indonesia. This model can also be replicated in other regions or further developed by incorporating additional indicators such as food security or social participation (Rajaratnam et al., 2010; Gelman et al., 2013; Badaruddin et al., 2020).

The results of the study also open up space for collaboration between academics, the government, and the private sector in the development of a digital dashboard based on poverty risk maps, thereby facilitating quick and targeted visualization and decision-making (Banerjee et al., 2014; Cressie & Wikle, 2011; Ananta et al., 2020).

Overall, a hierarchical Bayesian statistical approach with spatial and temporal integration has been shown to provide more accurate and contextual predictive results in understanding multidimensional poverty. This research is the initial foothold in the transition to a precise and adaptive microdata-based planning system in disadvantaged areas of Eastern Indonesia.

Conclusion

This study aims to develop a Hierarchical Bayesian statistical model capable of predicting multidimensional poverty patterns more accurately by incorporating spatial and temporal variations in disadvantaged villages in Eastern Indonesia. The results show that the model successfully captures the complexity of village-level poverty through the integration of key indicators such as access to clean water, sanitation, education, electricity, and asset ownership, demonstrating strong predictive performance characterized by low DIC values and high accuracy while effectively identifying high-risk clusters and significant temporal trends. Spatial analysis indicates that high-poverty-risk villages are predominantly concentrated in remote coastal areas, hilly regions, and locations with limited infrastructure, particularly in West Papua and parts of Southeast Maluku, while temporally, a notable increase in poverty risk occurred in 2020 due to the impact of the COVID-19 pandemic, which further exacerbated conditions in disadvantaged villages. Overall, this modeling approach provides a comprehensive risk and trend mapping framework that supports more precise, contextual, and adaptive village development policy planning, and academically contributes to the advancement of Bayesian-based spatial-temporal statistical models for micro socio-economic studies in Indonesia, with strong potential for replication in similar regions and research contexts.

Based on these findings, it is recommended that local governments and relevant ministries adopt this model as a decision-support tool in designing targeted poverty alleviation programs. Policymakers are encouraged to improve the availability and quality of village-level data to ensure more accurate modeling results. In addition, future research is suggested to expand the model by incorporating additional variables such as environmental, infrastructure, and socio-cultural factors, as well as applying mixed-method approaches to enrich the analysis. Continuous model validation using more recent data is also necessary to maintain its accuracy and adaptability in dynamic socio-economic conditions.

Reference

Alkire, S., & Santos, M. E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development, 59*, 251–274. https://doi.org/10.1016/j.worlddev.2014.01.026

Alkire, S., Kanagaratnam, U., & Suppa, N. (2021). The global multidimensional poverty index (MPI): 2021 update. *World Development, 146*, 105498. https://doi.org/10.1016/j.worlddev.2021.105498

Ananta, A., Arifin, E. N., & Hasbullah, M. S. (2020). Demographic and spatial patterns of poverty in Eastern Indonesia. *Indonesian Population Journal, 14*(2), 101–119.

Badaruddin, M., Hadi, S., & Wirawan, D. (2020). Spatial analysis of multidimensional poverty in Papua. *Journal of Indonesian Development Economics, 21*(1), 33–47. https://doi.org/10.24843/EPI.2020.v21.i01.p04

Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2014). *Hierarchical modeling and analysis for spatial data* (2nd ed.). Chapman and Hall/CRC.

Baş, H., & Kirişci, M. (2026). Fermatean fuzzy type entropy-based new integrated decision making method with analysis of energy poverty in Türkiye application. *arXiv Preprint arXiv:2602.21260*.

Central Statistics Agency. (2022). *Statistics of disadvantaged villages in Indonesia 2021*. BPS RI.

Cressie, N., & Wikle, C. K. (2011). *Statistics for spatio-temporal data*. John Wiley & Sons.

Dou, H., Ma, L., Liu, S., & Fang, F. (2022). Identification of rural regional poverty type based on spatial multi-criteria decision-making—Taking Gansu Province, an underdeveloped area in China, as an example. *Environment, Development and Sustainability, 24*(3), 3439–3460.

Fischer, M. M., & Wang, J. (2019). *Spatial data analysis: Models, methods and techniques*. Springer. https://doi.org/10.1007/978-3-662-54717-7

Firdausy, C. M., & Budisetyowati, D. A. (2022). Variables, dimensions, and indicators important to develop the multidimensional poverty line measurement in Indonesia. *Social Indicators Research, 162*(2), 763–802.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). *Bayesian data analysis* (3rd ed.). Chapman and Hall/CRC.

Kurniawan, H., & Dewi, M. S. (2021). Spatial inequality in village development in the eastern region of Indonesia. *Journal of Regional and Urban Development, 17*(2), 145–158.

Ministry of Agriculture and Rural Development. (2022). *Data and information on disadvantaged villages 2015–2021*. Ministry of Villages, Development of Disadvantaged Regions, and Transmigration of the Republic of Indonesia.

Padhiary, M., Saikia, P., Roy, P., Hussain, N., & Kumar, K. (2025). A review on advancing agricultural efficiency through geographic information systems, remote sensing, and automated systems. *Cureus Journal of Engineering, 2*, es44388-024.

Permanyer, I. (2018). A critical assessment of the UNDP's multidimensional poverty index. *World Development, 101*, 1–14. https://doi.org/10.1016/j.worlddev.2017.08.005

Pratama, R., & Sari, D. (2021). Determinants of poverty in Indonesia: A panel data analysis approach. *Journal of Economic Development, 46*(2), 123–137. https://doi.org/10.35866/caujed.2021.46.2.123

Pratomo, D. S., & Kuncoro, M. (2021). Evaluation of spatial-based multidimensional poverty alleviation policies. *Journal of Economics and Public Policy, 12*(1), 88–102.

Putri, S. R., Wijayanto, A. W., & Pramana, S. (2023). Multi-source satellite imagery and point of interest data for poverty mapping in East Java, Indonesia: Machine learning and deep learning approaches. *Remote Sensing Applications: Society and Environment, 29*, 100889.

Rajaratnam, J. K., Marcus, J. R., Flaxman, A. D., Wang, H., Levin-Rector, A., Dwyer, L., … Murray, C. J. (2010). Neonatal, postneonatal, childhood, and under-5 mortality for 187 countries, 1970–2010: A systematic analysis of progress towards Millennium Development Goal 4. *The Lancet, 375*(9730), 1988–2008. https://doi.org/10.1016/S0140-6736(10)60703-9

Surbakti, M. S., & Hadi, S. (2019). Spatial analysis of village poverty inequality in

Indonesia. *Journal of Development Planning: The Indonesian Journal of Development Planning, 3*(2), 102–119. https://doi.org/10.36574/jpp.v3i2.76

Suryahadi, A., Al Izzati, R., & Suryadarma, D. (2019). The impact of village fund on rural poverty and inequality in Indonesia. *Journal of Southeast Asian Economies, 36*(1), 1–19. https://doi.org/10.1355/ae36-1a

Wardhana, A., Nugroho, Y., & Kurniawati, L. (2022). Spatial analysis of poverty in eastern Indonesia: Evidence from Papua. *Regional Science Policy & Practice, 14*(3), 567–582. https://doi.org/10.1111/rsp3.12498

World Bank. (2022). *Indonesia poverty assessment: Toward a comprehensive approach to reducing poverty*. World Bank Group. https://openknowledge.worldbank.org/