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MODELING POVERTY SEVERITY INDEX IN EASTERN INDONESIA BASED ON NONPARARAMETRIC SPLINE TRUNCATED APPROACH FOR PANEL DATA

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ABSTRACT

Poverty severity remains a critical issue in Eastern Indonesia, where rates are consistently higher than in other regions. This study examines the Poverty Severity Index (P2) using parametric panel regression and nonparametric truncated splines for panel data across 17 provinces for the period 2020 to 2024. The predictor variables include per capita expenditure, mean years of schooling, and unmet need for health services. The secondary data were obtained from the official website of Central Bureau of Statistics (BPS). The parametric FEM produces a within R^2 of 36.9% and an MSE of 0.00912, which provides a baseline assessment of overall trends and global relationships among variables. In parallel, the first-order truncated spline model with two knot points which produces specific-province models, achieves an R^2 of 99.87% and an MSE of 0.00044. This model captures detailed province-specific patterns and nonlinearities and offers additional descriptive insight into regional variations in poverty severity. Together, these complementary approaches highlight both global and local dynamics and inform policy decisions that address economic, educational, and healthcare disparities in high-poverty regions especially in Eastern Indonesia.

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1. INTRODUCTION

Poverty remains a persistent challenge in developing countries like Indonesia, where national strategies often overlook regional disparities [1]. This is particularly evident in the eastern part of Indonesia—such as Papua, Maluku, Nusa Tenggara, Sulawesi, and Kalimantan—where poverty rates and development indicators have consistently lagged behind those in other regions. In 2023, the poverty rate reached 19.68 percent in Maluku–Papua, 13.29 percent in Nusa Tenggara, and 10.68 percent in Sulawesi. Moreover, from 2020 to 2024, Eastern Indonesia consistently recorded average Poverty Severity Index (P2) values above 0.5, peaking at 0.65 in 2020 and only declining modestly to 0.52 by 2024 [2]. In contrast, Western Indonesia remained stable within the range of 0.30 to 0.37. These figures show that poor households in Eastern Indonesia face deeper and more unequal poverty. Unlike the poverty headcount (P_0), the Poverty Severity Index (P_2) captures both depth and inequality, which also offering a more accurate basis for targeted and sustainable poverty policies [3].

Previous researchers have examined three dimensions of poverty, such as living standard, education, and health. For example, Hanandita &Tampubolon [4] included the role of per capita daily consumption as a reflection of living standard in measuring poverty, while Artha & Dartanto [5] included mean years of schooling to demonstrate the strong link between education and poverty. In the health domain, research by Jung [6] showed that poverty is strongly associated with increased unmet healthcare needs.

Regression models are commonly used to examine relationship between predictor and response variables. Parametric regression, such as linear or polynomial regression, relies on strict assumptions regarding the functional form and residual properties. These assumptions may limit the model if the true relationship deviates from specified form. However, parametric panel regression offers advantages in accounting for unobserved heterogeneity across individuals or regions and provides a parsimonious structure that facilitates interpretation and inference. In contrast, nonparametric regression provides greater flexibility by allowing the data to determine the relationship without strict functional assumptions [7]. Among these, spline regression offers both flexibility and interpretability. A truncated spline is a piecewise polynomial function segmented into multiple polynomial parts connected at specific knot point [8]. This form is enabling the model to capture complex patterns more effectively than ordinary polynomial functions. Predictor–response relationships, with nonparametric methods offering greater flexibility without strict functional assumptions. Several studies have applied nonparametric regression techniques in socio-economic research [9]-[17], including the use of spline functions for both modeling and interpreting welfare and poverty indicators [18]-[20]. Researchers have extended these approaches through the implementation of nonparametric longitudinal methods for analyzing panel data [21] - [25]. This is due to the advantages of panel data, which allow for the analysis of dynamic relationships while effectively accounting for individual heterogeneity compared to purely cross-sectional or time-series data [26]. However, the application of nonparametric regression especially using spline truncated model specifically to the Poverty Severity Index remains limited. A study [27] applied a parametric panel regression model to examine macroeconomic determinants of Poverty Severity Index in Indonesia. This study approach relied on generalized least squares and focused solely on macroeconomic determinants.

Therefore, the novelty of this study is the usage of a truncated spline regression model for panel data to analyze poverty severity in Eastern Indonesia and using predictors that represent expenditure as economic factor, healthcare access, and education which represents by mean years of schooling. The study applies both the spline approach and conventional panel regression, showing that the two methods provide complementary insights. While the panel regression captures overall trends and global relationships among variables, the province-specific spline model offers flexibility to describe detailed, nonlinear patterns within each region. This study also supports SDG No. 1 by offering a flexible, precise model that captures poverty severity and helping shape effective interventions in vulnerable regions like Eastern Indonesia. However, the limitations of this study are including the use of only five years of data, coverage of 17 provinces, and the application of a first-order spline with 1 or 2 knots to limit model complexity.

2. RESEARCH METHODS

2.1 Constructing the Dataset

This study utilizes secondary data obtained from the Indonesian Central Statistics Agency (*Badan Pusat Statistik*). The dataset comprises observations from 17 provinces located in Eastern Indonesia, as designated under Presidential Regulation No. 2 of 2015 concerning the National Medium-Term Development Plan 2015–2019. Data were collected annually over a five-year period from 2020 to 2024 which forming a balanced panel dataset. The analysis focuses on one response variable, the Poverty Severity Index, and three explanatory variables: adjusted per capita expenditure (X_1), mean years of schooling (X_2), and the percentage of unmet healthcare services (X_3).

The panel structure assumes that observations across different provinces are independent, while measurements taken over time within the same province are correlated [28]. Explicitly modelling cross-sectional dependence would substantially increase model complexity and is beyond the scope of the current spline-based framework. Consequently, one limitation of this study lies in the assumption of independence among cross-sectional units, and the findings should be interpreted as reflecting within-province relationships over time rather than spatial spillover effects. Future research may address this limitation by incorporating spatial or cross-sectional dependence structures to more explicitly capture inter-province interactions.

2.2 Estimating the Parametric Panel Regression Model

The parametric panel regression is a statistical approach that blends cross-sectional and time-series data to examine relationship over time and across different units. For $i = 1, 2, \ldots, N$ representing cross-sectional units, $t = 1, 2, \ldots, T$ denoting time periods, and $k = 1, 2, \ldots, p$ referring to predictor variables, the general form of the panel data regression equation is as follows:

$$y_{it} = \alpha_{it} + \sum_{k=1}^{p} \beta_{kit} X_{kit} + \varepsilon_{it}. \tag{1}$$

According to Gujarati [29], the panel regression model has three types, Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM).

1. Common Effect Model is the simplest model that assuming a constant intercept and slope for all cross-sectional units and time periods. The general equation of the CEM is as follows.
$$y_{it} = \alpha + \sum_{k=1}^{p} \beta_k X_{kit} + \varepsilon_{it}. \tag{2}$$
2. Fixed Effect Model, also referred to as the Least Squares Dummy Variable (LSDV) regression model, which assumes that the slope coefficients remain constant while the intercept varies across cross-sectional units. The FEM approach is formulated as follows.
$$y_{it} = \alpha_i + \sum_{k=1}^{p} \beta_k X_{kit} + \varepsilon_{it}. \tag{3}$$
3. Random Effect Model assumes that individual effect remains constant over time but are uncorrelated with the predictor variables. The REM is expressed as follows.
$$y_{it} = \alpha_{it} + \sum_{k=1}^{p} \beta_k X_{kit} + \omega_{it}, \tag{4}$$
where $\omega_{it} = u_i + \varepsilon_{it}$ and u_i denotes the unobserved individual effect of the *i*-th units.

2.3 Defining Nonparametric Spline Truncated Regression Model

A spline truncated is a piecewise polynomial function that is segmented into several different polynomial parts, which are then connected at specific knot points and making it more flexible than an ordinary polynomial function [8]. Given a set of data pairs (x_i, y_i), where i = 1,2, ..., n assumed to follow a nonparametric regression function. Then, the univariate spline truncated function of order q with k knots $\tau_1, \tau_2, \ \dots\ , \tau_k$ is defined as [30]:

$$f(x_i) = \sum_{h=0}^{q} \alpha_h x_i^h + \sum_{r=1}^{k} \beta_{q+r}(x_i - \tau_r)_+^q. \tag{5}$$

The Eq. (5) can be extended to the case of multiple predictors spline regression. For a dataset with multiple predictors $(x_{1i}, x_{2i}, \dots, x_{pi}, y_i)$, the general form of a nonparametric multipredictor regression is:

$$y_i = \sum_{j=1}^{p} f(x_{ji}) + \varepsilon_i, \tag{6}$$

where

$$f(x_{ji}) = \sum_{h=0}^{q} \alpha_{jh} x_{ji}^h + \sum_{r=1}^{k} \beta_{j(q+r)}(x_{ji} - \tau_{jr})_+^q. \tag{7}$$

By substituting Eq. (7) to Eq. (6), we obtain the multiple predictors spline regression model with order q, k knot points, and p predictors as follows:

$$y_i = \sum_{j=1}^{p}\left(\sum_{h=0}^{q} \alpha_{jh} x_{ji}^h + \sum_{r=1}^{k} \beta_{j(q+r)}(x_{ji} - \tau_{jr})_+^q\right) + \varepsilon_i,$$

$$y_i = \sum_{j=1}^{p}\sum_{h=0}^{q} \alpha_{jh} x_{ji}^h + \sum_{j=1}^{p}\sum_{r=1}^{k} \beta_{j(q+r)}(x_{ji} - \tau_{jr})_+^q + \varepsilon_i,$$

$$y_i = \alpha_0^* + \sum_{j=1}^{p}\sum_{h=1}^{q} \alpha_{jh} x_{ji}^h + \sum_{j=1}^{p}\sum_{r=1}^{k} \beta_{j(q+r)}(x_{ji} - \tau_{jr})_+^q + \varepsilon_i. \tag{8}$$

where α and β are real numbers [31] and $\alpha_0^* = \sum_{j=1}^{p} \alpha_{j0}$.

The truncated function $(x_{ji} - \tau_{jr})_+^q$ is defined as

$$(x_{ji} - \tau_{jr})_+^q = \begin{cases} (x_{ji} - \tau_{jr})^q, & x_{ji} \geq \tau_{jr} \\ 0 \quad , & x_{ji} < \tau_{jr} \end{cases}, \tag{9}$$

where $\tau_{j1}, \tau_{j2}, \dots, \tau_{jk}$ are the knot points that indicate changes in the curve's behavior across different subintervals [32].

2.4 Defining Nonparametric Spline Truncated Regression Model for Panel Data

Suppose we have $i = 1,2, \dots, m$ individuals who are observed repeatedly over specific time periods $j = 1,2, \dots, n$, then the spline function of order q with k knots and one predictor variable is formulated as

$$y_{ij} = \sum_{h=0}^{q} \alpha_{hi} x_{ij}^h + \sum_{r=1}^{k} \beta_{ri}(x_{ij} - \tau_{ri})_+^q + \varepsilon_{ij}. \tag{10}$$

The Eq. (10) can be extended to include p predictors, as follows:

$$y_{ij} = \sum_{l=1}^{p} f_l(x_{ij}) + \varepsilon_{ij},$$

$$y_{ij} = \sum_{l=1}^{p}\left(\sum_{h=0}^{q} \alpha_{hil} x_{ijl}^h + \sum_{r=1}^{k} \beta_{ril}(x_{ijl} - \tau_{ril})_+^q\right) + \varepsilon_{ij}. \tag{11}$$

2.5 Estimating the Parameter of Nonparametric Spline Truncated Regression for Panel Data

Eq. (11) can be rewritten in matrix form as follows.

$$\boldsymbol{y} = \boldsymbol{X_\tau \beta} + \boldsymbol{\varepsilon},$$

$$\begin{pmatrix} \boldsymbol{y_1} \\ \boldsymbol{y_2} \\ \vdots \\ \boldsymbol{y_m} \end{pmatrix} = \begin{pmatrix} \boldsymbol{X_1(\tau_1)} & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{X_2(\tau_2)} & \cdots & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \cdots & \boldsymbol{X_m(\tau_m)} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta_1} \\ \boldsymbol{\beta_2} \\ \vdots \\ \boldsymbol{\beta_m} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon_1} \\ \boldsymbol{\varepsilon_2} \\ \vdots \\ \boldsymbol{\varepsilon_m} \end{pmatrix}. \tag{12}$$

where

$\boldsymbol{y_1} = (y_{11}, y_{12}, \dots, y_{1n})',$

$\vdots$

$\boldsymbol{y_m} = (y_{11}, y_{12}, \dots, y_{mn})'.$

For a first-order spline truncated panel data model, the resulting design matrix when using p predictors and k knot points is as follows.

$$\boldsymbol{X_1(\tau_1)} = \begin{bmatrix} 1 & x_{111} & x_{121} & \cdots & x_{1p1} & (x_{111}-\tau_{111}) & \cdots & (x_{111}-\tau_{11k}) & \cdots & (x_{1p1}-\tau_{1p1}) & \cdots & (x_{1p1}-\tau_{1pk}) \\ 1 & x_{112} & x_{122} & \cdots & x_{1p2} & (x_{112}-\tau_{111}) & \cdots & (x_{112}-\tau_{11k}) & \cdots & (x_{1p2}-\tau_{1p1}) & \cdots & (x_{1p2}-\tau_{1pk}) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & x_{11n} & x_{12n} & \cdots & x_{1pn} & (x_{11n}-\tau_{111}) & \cdots & (x_{11n}-\tau_{11k}) & \cdots & (x_{1pn}-\tau_{1p1}) & \cdots & (x_{1pn}-\tau_{1pk}) \end{bmatrix},$$

$\vdots$

$$\boldsymbol{X_m(\tau_m)} = \begin{bmatrix} 1 & x_{m11} & x_{m21} & \cdots & x_{mp1} & (x_{m11}-\tau_{m11}) & \cdots & (x_{m11}-\tau_{m1k}) & \cdots & (x_{mp1}-\tau_{mp1}) & \cdots & (x_{mp1}-\tau_{mpk}) \\ 1 & x_{m12} & x_{m22} & \cdots & x_{mp2} & (x_{m12}-\tau_{m11}) & \cdots & (x_{m12}-\tau_{m1k}) & \cdots & (x_{mp2}-\tau_{mp1}) & \cdots & (x_{mp2}-\tau_{mpk}) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & x_{m1n} & x_{m2n} & \cdots & x_{mpn} & (x_{m1n}-\tau_{m11}) & \cdots & (x_{m1n}-\tau_{m1k}) & \cdots & (x_{mpn}-\tau_{mp1}) & \cdots & (x_{mpn}-\tau_{mpk}) \end{bmatrix}.$$

And the vector $\boldsymbol{\beta}$ containing

$\boldsymbol{\beta_1} = (\alpha_0, \alpha_{11}, \alpha_{12}, \dots, \alpha_{1p}, \beta_{11}, \beta_{12}, \dots, \beta_{1k})',$

$\vdots$

$\boldsymbol{\beta_m} = (\alpha_0, \alpha_{m1}, \alpha_{m2}, \dots, \alpha_{mp}, \beta_{m1}, \beta_{m2}, \dots, \beta_{mk})'.$

To solve Eq. (12) above, the weighted least squares method is used by minimizing the weighted sum of squared errors. We adopt one of the weighting scheme proposed by Wu and Zhang [33]. The weighting matrix in this study are assigned as $\boldsymbol{W} = \left[diag\left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right)\right]$ where n is the number of observations within each individual. Under this specification, the estimator remains equivalent to ordinary least squares up to a scaling factor while ensuring that the total influence of each unit remains comparable. The estimation equations is as follows [34].

$$\begin{aligned} \boldsymbol{\varepsilon' W \varepsilon} &= \boldsymbol{(y - X_\tau \beta)' W (y - X_\tau \beta)}, \\ G(\boldsymbol{\beta}) &= \boldsymbol{y'Wy - y'WX_\tau\beta - \beta'X_\tau'Wy + \beta'X_\tau'WX_\tau\beta}, \\ \frac{\boldsymbol{d}}{\boldsymbol{d\beta}} \boldsymbol{G(\beta)} &= \boldsymbol{0}, \\ \boldsymbol{-2X_\tau'Wy + 2\beta X_\tau'WX_\tau} &= \boldsymbol{0}, \\ \boldsymbol{\beta X_\tau'WX_\tau} &= \boldsymbol{X_\tau'Wy}, \\ \boldsymbol{\hat{\beta}} &= \boldsymbol{(X_\tau'WX_\tau)^{-1}X_\tau'Wy}. \end{aligned} \tag{13}$$

The estimated coefficient vector, denoted as $\boldsymbol{\hat{\beta}}$ in Eq. (13) can be simplified into the following form:

$$\boldsymbol{\hat{\beta}} = \boldsymbol{A(h)y},$$

where

$$\boldsymbol{A(h)} = \boldsymbol{(X_\tau'WX_\tau)^{-1}X_\tau'W}. \tag{14}$$

Although the estimation is implemented within a unified matrix formulation, the model allows each province to have its own set of spline parameters and knot locations. Therefore, the proposed approach is more appropriately interpreted as a collection of province-specific spline models estimated simultaneously, rather than a single global panel model with shared parameters. This formulation enables the model to capture heterogeneity in the functional relationships across provinces while maintaining computational efficiency within a single estimation framework.

2.6 Selecting Optimal Model

The optimal knot points were determined using the Generalized Cross Validation (GCV) method, which identifies the best knot configuration by minimizing prediction error while controlling model complexity [35], [36]. In this research, candidate knots were generated as 30 equally spaced points within the observed range of each predictor, excluding boundary values, and resulting in 28 candidates for each predictor–province combination.

Knot selection was conducted under a pooled framework using all longitudinal observations. A common index over the candidate knots was applied simultaneously across all predictors and provinces, where each index represents a global knot configuration. For the one-knot model, 28 candidate configurations were evaluated, while for the two-knot model, all pairwise combinations (378 models) were considered. The optimal configuration was selected based on the minimum GCV value. The equation used to compute the GCV is presented below [31].

$$GCV(h) = \frac{MSE(h)}{\left[\frac{1}{mn} tr\left(\boldsymbol{I} - \boldsymbol{A}(\boldsymbol{h})\right)\right]^2}, \tag{15}$$

$$MSE(h) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(y_{ij} - \hat{y}_{ij}\right)^2. \tag{16}$$

Where m is the number of individuals and n is the number of time periods observed. The optimal knot value is the one that produces the smallest GCV value.

3. RESULTS AND DISCUSSION

3.1 Data Exploration

Based on the acquired secondary data, an examination of the overall characteristics of the dataset was conducted through descriptive statistical analysis. The results of the descriptive statistics are presented in Table 1 below.

Table 1. Statistic Descriptive of Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Poverty Severity Index (Y)	0.598	0.519	0.110	2.15
Average expenditure per capita (X_1)	10063	1603	6954	13793
Mean years of schooling (X_2)	8.606	0.894	6.690	10.26
Percentage of unmet need for healthcare services (X_3)	5.759	1.86	2.160	10.21

Based on the Table 1, it can be observed that the response variable poverty severity index (Y) has a mean of 0.598 and a median of 0.440. This indicates the presence of several extreme values on the right tail of distribution, or high index values. The standard deviation is 0.519, which is relatively close to the mean, suggesting a considerable degree of variability in poverty severity across regions and over different time periods. Additionally, the wide range between the maximum and minimum values (representing high and low poverty severity) indicates the existence of significant disparities in poverty severity among regions in Eastern Indonesia.

Following this, a time series graph illustrating the poverty severity index from 2020 to 2024 across provinces in Eastern Indonesia is show in Fig. 1 below.

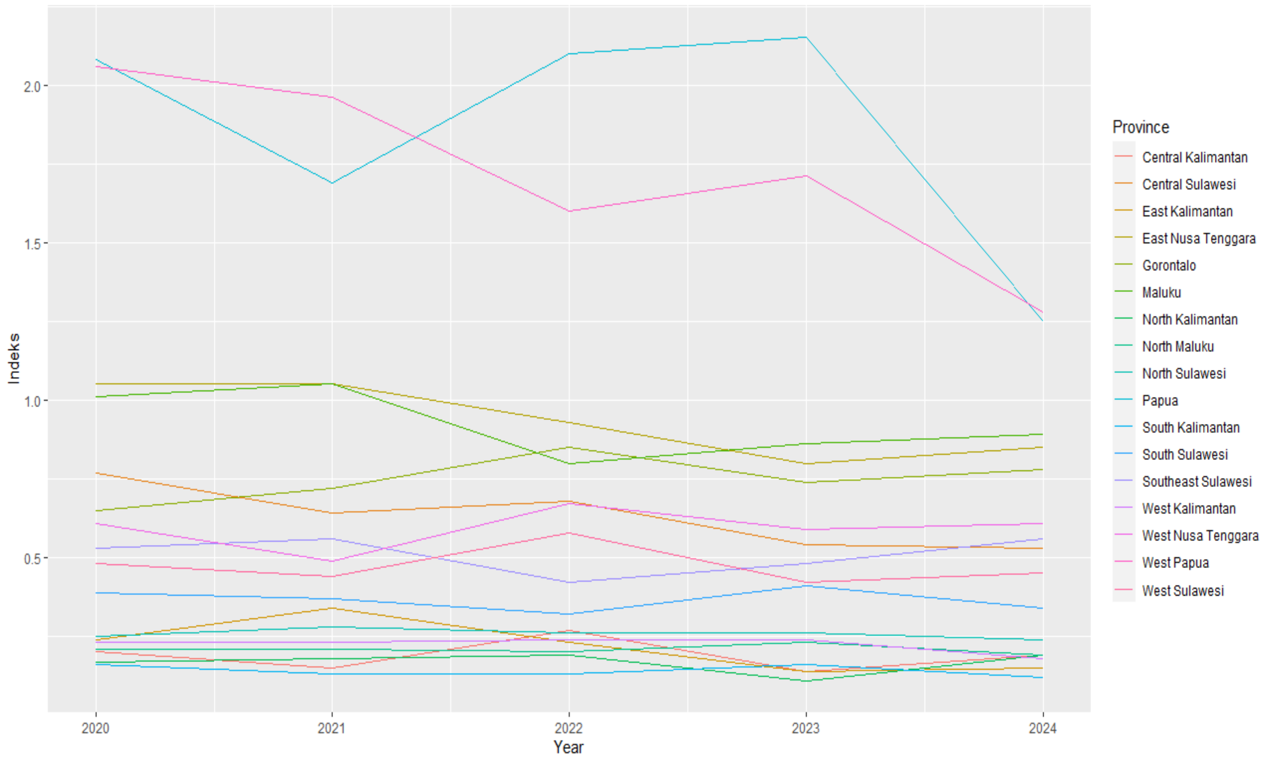

Figure 1. Trend of the Poverty Severity Index in each Province

Based on Fig. 1, Papua and West Papua show a decreasing trend, these two provinces consistently have the highest Poverty Severity Index across all years compared to other provinces. However, when observing the overall trend, the majority of provinces in Eastern Indonesia have experienced a decline in poverty severity over time.

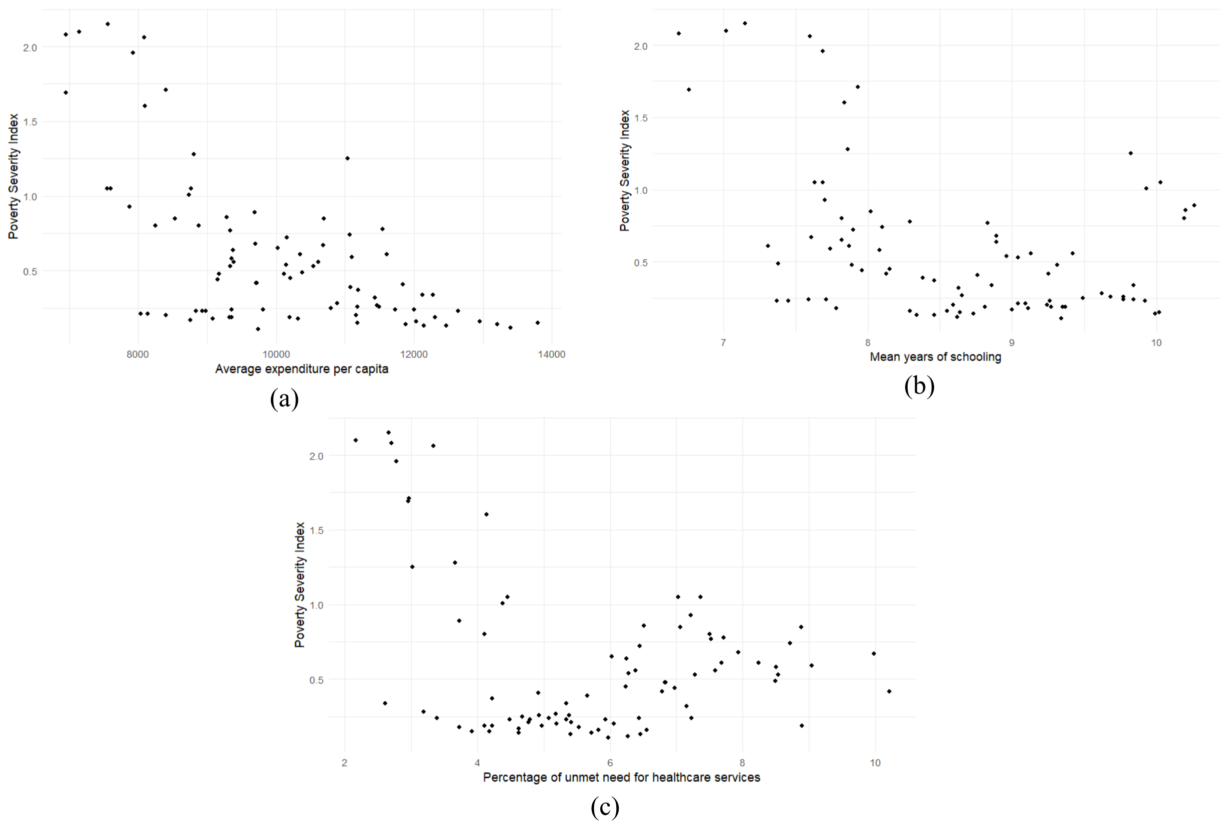

Figure 2. Scatterplot of the Response Variable in Relation to Predictor Variables: (a) Per Capita Expenditure, (b) Average Years of Schooling, and (c) Percentage of Unmet Need for Health Services

To understand the structure and characteristics of the panel data, an exploration was conducted based on correlation values. Fig. 3 presents the correlation matrix between subjects used in this study. Although several provinces, namely East Nusa Tenggara, East Kalimantan, West Kalimantan, Papua, West Sulawesi, and Central Kalimantan, show significant correlations with other provinces, the panel data assumes independence across individuals. Therefore, this study continues to use all 17 provinces as units of observation.

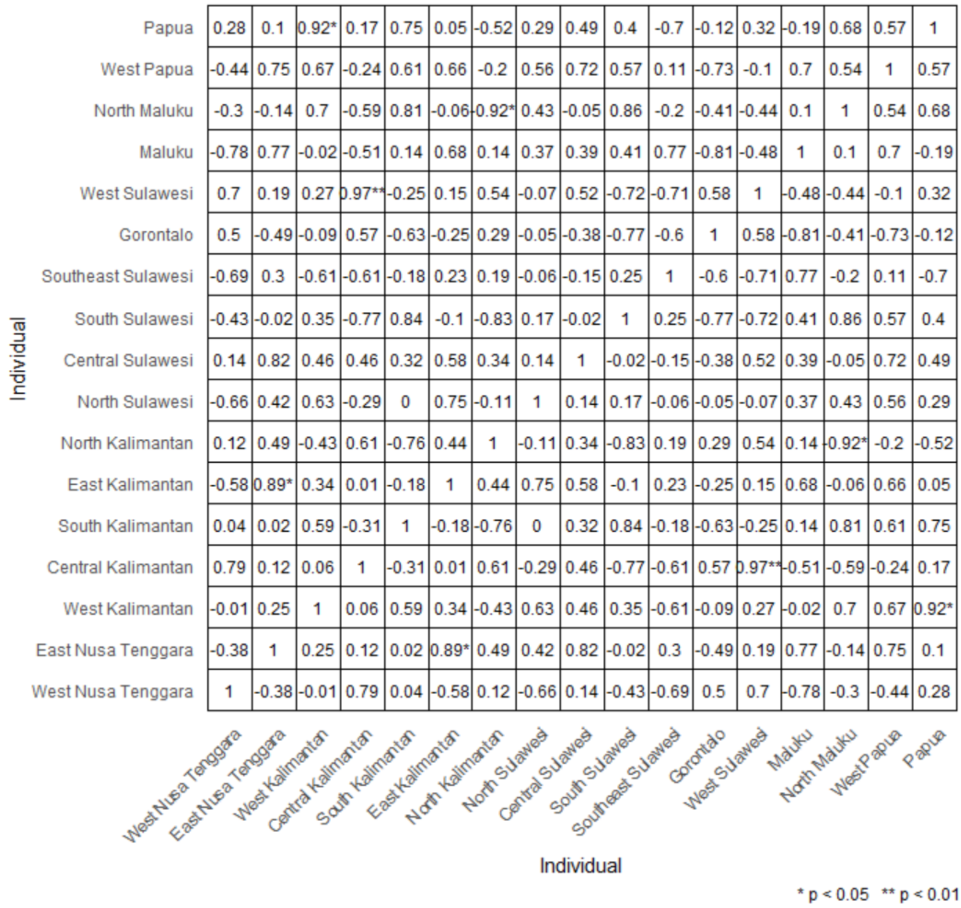

Figure 3. Inter-individual Correlation

In addition, the correlation across time for the Poverty Severity Index variable, as shown in Fig. 3 and Fig. 4, reveals a strong positive relationship, with Pearson correlation values ranging from 0.94 to as high as 0.99. This indicates a strong dependency in repeated measurements within the same individuals over time.

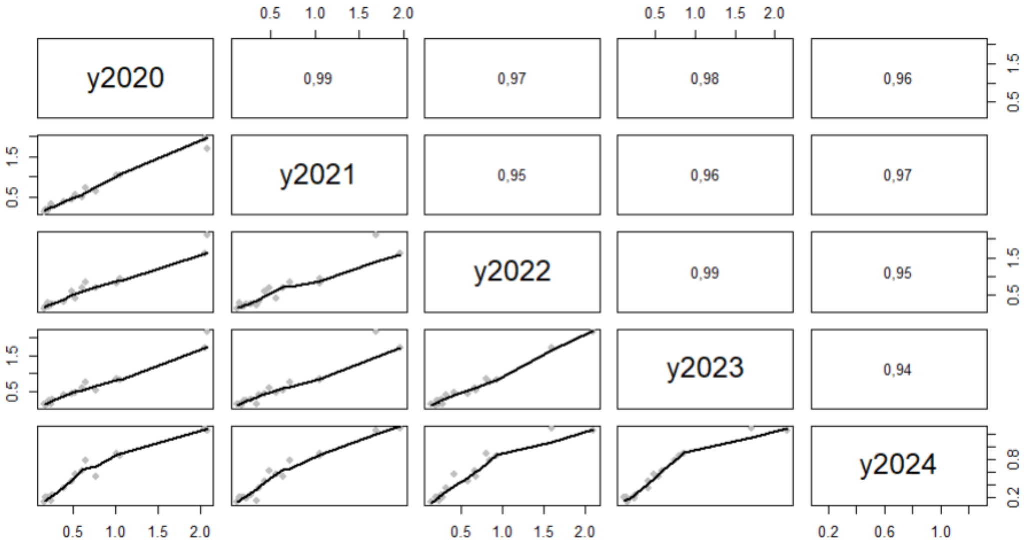

Figure 4. Temporal Correlation of the Poverty Severity Index Variable

3.2 Parametric Panel Regression Model

The panel regression analysis began by estimating CEM, FEM, and REM. To determine the most appropriate specification, a Chow Test was applied to compare CEM and FEM (F = 52.965, p-value = 0.000), and followed by a Haussman Test to distinguish between FEM and REM (χ^2 = 56.512, p-value = 0.000). Both tests indicated that the Fixed Effect Model is the most suitable. Based on these results, FEM is selected as the final model, and the following Eq. (17) presents its estimation outcomes.

$$\hat{y}_{it} = \hat{\alpha}_i - 3.3311 \times 10^{-6} X_{1it} - 0.22698 X_{2it} - 1.8034 \times 10^{-3} X_{3it} \tag{17}$$

Where $\hat{\alpha}_i$ represents the individual-specific effect. To further asses the validity and applicability of the model, the residual assumption $N \sim (0, \sigma^2)$ has to be examined. This FEM model yielded a within R^2 of 36.9% and a MSE of 0.00912. The Kolmogorov-Smirnov test was employed to determine whether the residuals follow a normal distribution, while the Breusch-Pagan test was conducted to assess the homogeneity of residual variance. The normality test yielded a statistic of $D = 0.1538$ with a p-value of 0.078 which exceeding the 5% significance level. It indicates that the residuals are normally distributed. In contrast, the Breusch-Pagan test produced a statistic of $BP = 19.872$ with a p-value of 0.0001 below the 5% significance level. It can be concluded that the variance of residual is not constant. These results indicate that, while the normality assumption is reasonably satisfied, the homogeneity of variance assumption is violated. In this context, the findings from the FEM model should be interpreted with caution. Rather than serving as a direct benchmark for model comparison, the parametric specification provides a complementary perspective on the data. Alternative modelling approaches, including more flexible frameworks such as nonparametric regression, may also be considered to explore potential nonlinearities and heterogeneous relationships without relying on strict parametric assumptions.

3.3 Determining the Optimum Knot Point for Nonparametric Spline Truncated Model

A first-order truncated spline model was chosen over higher-order spline alternatives due to considerations of model parsimony, interpretability, and the limited time dimension of the panel data. First-order truncated splines provide a more stable functional representation when sample size and temporal variation are limited, which can avoid the risks of overfitting and inflated parameter uncertainty that can arise with higher-order specifications [37]. Moreover, the linear basis of a first-order spline enhances interpretability, which can allow clear interpretation of marginal effects across thresholds without the added complexity and potential multicollinearity associated with higher-order polynomial terms.

The best spline truncated nonparametric regression model is identified by the minimum Generalized Cross Validation (GCV). This study compares models with one and two first-order knots. GCV values are analyzed for adjusted per capita expenditure, mean years of schooling, and percentage of unmet need of healthcare services as predictors of the Poverty Severity Index. Table 2 and Table 3 below present knot points based on the minimum GCV values.

Table 2. Output Based on Minimum GCV 1 Knot

Province	Knot			GCV
	X_1	X_2	X_3	
West Nusa Tenggara	10740.482	7.483	8.393	3.4347×10^{-7}
East Nusa Tenggara	7858.138	7.751	7.175	
West Kalimantan	9361.689	7.497	5.333	
Central Kalimantan	11510.586	8.658	4.763	
South Kalimantan	`1456.241	8.392	5.756	
East Kalimantan	12368.862	9.847	3.457	
North Kalimantan	9203.206	9.108	5.334	
North Sulawesi	11165.586	9.598	3.869	
Central Sulawesi	9707.724	8.895	6.771	
South Sulawesi	11450.172	8.528	5.129	
Southeast Sulawesi	9726.689	9.157	7.568	
Gorontalo	10491.413	7.965	6.917	
West Sulawesi	9480.413	7.970	6.941	
Maluku	9027.448	10.032	4.592	
North Maluku	8431.724	9.142	4.589	
West Papua	8200.862	7.702	3.202	
Papua	8221.137	7.661	2.426	

Each program run generated multiple knot alternatives with varying GCVs. Table 2 shows that the optimal single-knot model achieved the lowest GCV of 3.4347×10^{-7} out of 28 alternatives. Meanwhile, Table 3 shows the optimal two-knot model with a minimum GCV of 1.138994×10^{-7} from 378 alternatives. Comparing the lowest GCV values between one-knot and two-knot models, the two-knot configuration yielded the best result with the lowest GCV 1.138994×10^{-7} and MSE 0.0004378291. In this case where only two knots are specified, each spline function for the explanatory variable $X_l(l = 1,2,3)$ is partitioned into three distinct segments: the initial segment preceding the first knot, the intermediate segment located between the two knots, and the final segment following the second knot. This structure enables the model to adequately capture nonlinear relationship within the data while preserving parsimony in model specification.

Table 3. Output Based on Minimum GCV 2 Knot

Province	Knot			GCV
	X_1	X_2	X_3	
West Nusa Tenggara	10956.86	7.580	8.790	1.1389×10^{-7}
	11129.97	7.657	9.107	
East Nusa Tenggara	8027.103	7.818	7.256	
	8162.276	7.872	7.321	
West Kalimantan	9601.517	7.567	5.807	
	9793.379	7.624	6.186	
Central Kalimantan	11708.69	8.696	5.087	
	11867.17	8.726	5.346	
South Kalimantan	12691.93	8.449	5.955	
	12880.48	8.494	6.113	
East Kalimantan	12724.9	9.890	3.927	
	13009.72	9.925	4.304	
North Kalimantan	9451.655	9.168	6.225	
	9650.414	9.217	6.938	
North Sulawesi	11373.69	9.658	4.247	
	11540.17	9.707	4.549	
Central Sulawesi	9914.793	8.931	7.061	
	10080.45	8.960	7.292	
South Sulawesi	11656.38	8.611	5.634	
	11821.34	8.677	6.038	
Southeast Sulawesi	9946.517	9.223	8.228	
	10122.38	9.275	8.757	
Gorontalo	10753.31	8.046	7.410	
	10962.83	8.111	7.805	
West Sulawesi	9662.31	8.015	7.331	
	9807.828	8.051	7.642	
Maluku	9191.586	10.089	5.072	
	9322.897	10.134	5.455	
North Maluku	8653.793	9.199	4.794	
	8831.448	9.244	4.958	
West Papua	8351.897	7.759	3.436	
	8472.724	7.804	3.624	
Papua	8925.103	8.201	2.575	
	9488.276	8.632	2.693	

Overall, the truncated spline panel data model with two knots for the Poverty Severity Index in Eastern Indonesia is considered appropriate, as it yields a relatively small error, as indicated by the low Mean Squared Error (MSE) value of 0.0004378. The model also achieves a high coefficient of determination (R^2) of 99.835%. This indicates that 99.835% of the variability in the Poverty Severity Index can be explained by the predictor variables, within the truncated spline panel data model with two knots, while the remaining 0.165% is attributed to other factors not included in the model.

The relatively short time dimension of the panel (2020–2024) may raise concerns regarding the reliability and potential overfitting of flexible nonparametric models. With limited temporal observations per province, spline-based approaches can more easily conform to within-sample variation and potentially inflating goodness-of-fit measures such as R^2. However, several aspects of the modeling strategy mitigate this concern. First, model complexity was explicitly constrained by restricting the spline to first-order functions and limiting the number of knots to a maximum of two per predictor. Second, knot selection was based on the Generalized Cross Validation (GCV) criterion, which penalizes excessive flexibility and discourages overfitting even in relatively small samples as demonstrated by [38] and [39]. Third, the empirical results demonstrate stability, as the R^2 values remain consistently high and do not differ substantially between one-knot (R^2 = 99.702%) and two-knot (R^2 = 99.835%) specifications, nor are they sensitive to reductions in the candidate knot set. These findings suggest that the model captures stable underlying patterns rather than idiosyncratic noise. Nevertheless, given the limited sample size, the results should be interpreted primarily as descriptive of within-sample provincial dynamics, and caution is warranted in extending the findings to out-of-sample prediction or long-term generalization.

3.4 Estimating the Parameters

Since the selected model is a first-order spline with two knots, the total number of estimated parameters is 170 across all 17 provinces. This implies that each province has 10 distinct parameters, including 1 intercept, 3 main coefficients, 3 first-knot spline coefficients, and 3 second-knot spline coefficients. As an example, Maluku is selected to interpret the spline truncated regression model with two knots due to fluctuations in its Poverty Severity Index from 2020 to 2024. Given that each province has its own set of estimated parameters and knot locations, the results for Maluku provide a representative example of how the model captures localized nonlinear patterns. Table 4 shows the parameter estimates based on the optimal knot points.

Table 4. Maluku Province Model Parameter Estimation

$\alpha_{14;0}$	$\alpha_{14;1}$	$\alpha_{14;2}$	$\alpha_{14;3}$	$\beta_{14;11}$	$\beta_{14;12}$	$\beta_{14;21}$	$\beta_{14;22}$	$\beta_{14;31}$	$\beta_{14;32}$
0.0222	-0.0001	-0.1003	0.5909	-0.0153	0.0220	-0.1603	-0.0878	-0.0008	-0.0006

Based on the estimated parameters of the spline truncated panel data model for Maluku Province in Table 4 above, the resulting Eq. (18) is as follows.

$$\begin{aligned}\hat{y}_j = {} & 0.0222 - 0.0001X_{1j} - 0.1003X_{2j} + 0.5909X_{3j} \\ & -0.0153(X_{1j} - 9191.586)_+ + 0.0220(X_{1j} - 9322.897)_+ \\ & -0.1603(X_{2j} - 810.08931)_+ - 0.0878(X_{2j} - 10.13483)_+ \\ & -0.0008(X_{3j} - 5.072069)_+ - 0.0006(X_{3j} - 5.455517)_+.\end{aligned} \tag{18}$$

If the other predictor variables besides Expenditure per Capita (X_1) are assumed to be constant, then Eq. (18) above can be rewritten as follows.

$$\widehat{y_j} = \begin{cases} 0.022235049 - 0.0000684896X_{1j}. & X_{1j} < 9191.586 \\ 140.9540 - 0.01540119X_{1j}. & 9191.586 \le X_{1j} < 9322.897. \\ -64.165047 + 0.00660046X_{1j}. & X_{1j} \ge 9322.897 \end{cases} \tag{19}$$

If the other predictor variables besides Average Years of Schooling (X_2) are assumed to be constant, then Eq. (18) above can be rewritten as follows

$$\widehat{y_j} = \begin{cases} -0.022235049 - 0.1003490X_{2j} & X_{2j} < 10.08931 \\ 1.639596 - 0.26065341X_{2j}. & 10.08931 \le X_{2j} < 10.13483. \\ 2.52982356 - 0.34849188X_{2j}. & X_{2j} \ge 10.13483 \end{cases} \tag{20}$$

If the other predictor variables besides Percentage of Unmet Need for Healthcare Services (X_3) are assumed to be constant, then Eq. (18) above can be rewritten as follows

$$\widehat{y_j} = \begin{cases} 0.022235049 + 0.590916X_{2j} & X_{3j} < 5.072069 \\ 0.0260613 + 0.590162033X_{3j}. & 5.072069 \le X_{3j} < 5.455517. \\ 0.029079343 + 0.58960882X_{3j}. & X_{3j} \ge 5.455517 \end{cases} \tag{21}$$

3.5 Interpretating the Best Spline Model

Based on the constructed and estimated spline truncated regression model, the following interpretations provide a detailed explanation of how each predictor variable contributes to variations in the Poverty Severity Index across Maluku Province, Indonesia.

1. Interpretation of the Effect of Per Capita Expenditure (X_1) on the Poverty Severity Index in Maluku Province
   In the case of Maluku Province, the relationship between per capita expenditure and the Poverty Severity Index (P2) is nonlinear. When per capita expenditure is below Rp9,191.586, every additional one thousand rupiah reduces the index by approximately 0.000068489 units. If expenditure falls between Rp9,191.586 and Rp9,322.897, the index decreases more significantly by around 0.01540119 units. However, once expenditure exceeds Rp9,322.897, each one thousand rupiah increase instead raises the index by about 0.0066046 units.
   The nonlinear pattern observed in Maluku Province can be explained by differences in how increases in per capita expenditure translate into welfare gains across expenditure levels. At lower and intermediate expenditure ranges, additional spending likely reflects improved access to basic necessities, which aligns with studies showing that higher per capita expenditure contributes to poverty reduction when it enhances purchasing power among lower-income households [40], [41]. However, beyond a certain threshold, further increases in per capita expenditure may not be accompanied by proportional income growth and may instead be driven by rising prices or consumption concentrated among higher-expenditure groups. As suggested by [42], aggregated expenditure measures can mask underlying inequality, while inflationary pressures can increase consumption costs without improving real welfare, thereby intensifying poverty severity [43]. This explains why higher expenditure at upper levels is associated with an increase in the Poverty Severity Index in Maluku Province.

2. Interpretation of the Effect of Average Years of Schooling (X_2) on the Poverty Severity Index in Maluku Province
   In the case of the Poverty Severity Index in Maluku Province, if the average years of schooling is less than 10.089 years, each additional year of schooling reduces the index by approximately 0.100349 units. When the average years of schooling falls between 10.089 and 10.134 years, each one-year increase leads to a reduction of about 0.26065341 units. If the average exceeds 10.134 years, every additional year of schooling decreases the Poverty Severity Index by approximately 0.34893188 units. These findings are consistent with the theoretical framework discussed in the previous chapter, which states that there is a negative relationship between average years of schooling and the Poverty Severity Index.
   The strengthening negative effect of average years of schooling on the Poverty Severity Index across higher schooling levels in Maluku Province indicates that education becomes more effective in reducing poverty severity once basic educational attainment has been achieved. At lower schooling levels, additional education mainly improves fundamental skills and produces relatively limited reductions in poverty severity, while at higher schooling thresholds education enhances access to better employment opportunities and income stability, which substantially reduces inequality among poor households. This pattern is consistent with empirical evidence showing that secondary education has a stronger poverty-reducing effect than primary education alone [44], [45].

3. Interpretation of the Effect of Percentage of Unmet Need for Healthcare Services (X_3) on the Poverty Severity Index in Maluku Province
   In the case of the Poverty Severity Index in Maluku Province, when the percentage of unmet need for healthcare services is below 5.072069%, a one-percent-point increase in unmet need raises the index by approximately 0.590916 units. When the percentage lies between 5.072% and 5.455%, a one-percent-point increase results in an increase of about 0.590162 units in the index. If the percentage of unmet need exceeds 5.455%, a one-percent-point increase leads to a rise of approximately 0.5896088 units in the Poverty Severity Index.
   The positive relationship between unmet healthcare needs and the Poverty Severity Index can be justified by evidence that barriers to accessing necessary health services disproportionately affect economically vulnerable households. A study show that unmet healthcare needs are strongly associated with income-related inequality, where individuals in lower socioeconomic groups face

higher unmet needs and greater exposure to health-related financial risks [46]. Limited access to healthcare increases out-of-pocket expenditures and reduces the capacity of poor households to cope with illness, thereby deepening disparities among the poor [47]. This mechanism explains why increases in unmet healthcare needs consistently raise poverty severity across different threshold levels, as captured by the spline model.

3.6 Thematic Classification Map

The following presents a thematic map of province groupings in Eastern Indonesia for each predictor, based on the sign of the coefficients obtained from the estimation results using the two-knot spline truncated panel data model.

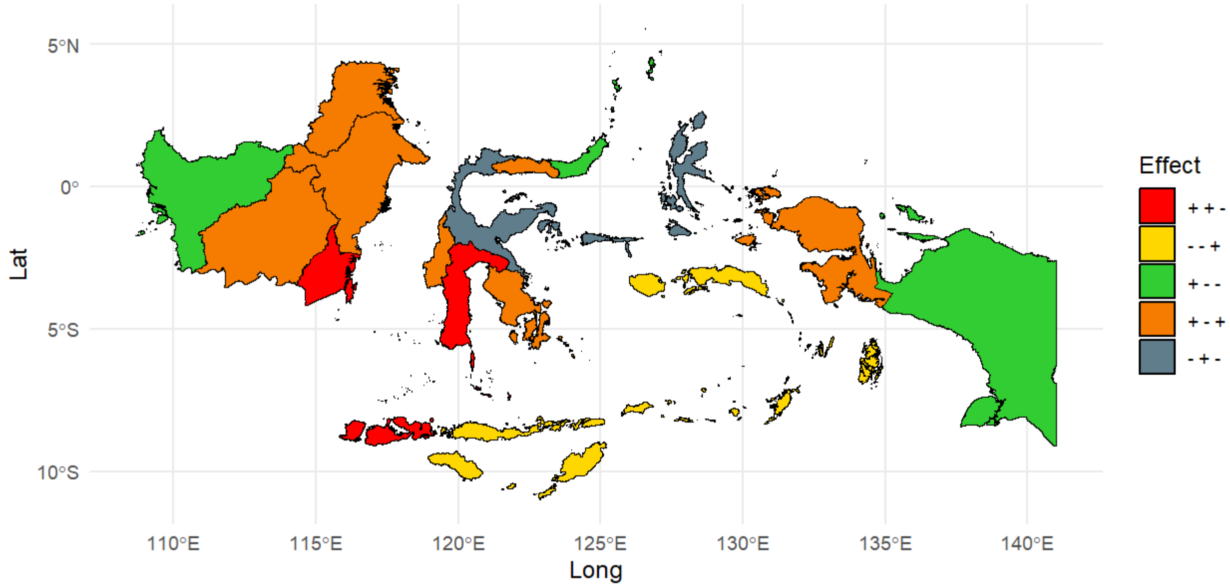

Figure 5. The Effect of X_1 on the Poverty Severity Index
(*Generated using RStudio*)

Fig. 5 illustrates the spatial variation in the effect of X_1 on the Poverty Severity Index across provinces in Eastern Indonesia. Each estimated effect corresponds to the three-segments spline representation, where the sign pattern, positive or negative, indicates the direction of the influence in each segment determined by the two-knot points. For example, in the Province of Papua, the pattern $(+--)$ suggests that at lower levels of X_1, the variable exerts a positive influence on the Poverty Severity Index, indicates that an increase in X_1 initially intensifies poverty severity. However, as X_1 exceeds the first knots, the effect turns negative and remains so in the higher segments. It implies that further increases in X_1 contribute to poverty severity reduction. Subsequently, Fig. 6 presents the spatial distribution of the effect of X_2 and allows for a comparative assessment of whether similar or distinct nonlinear patterns emerge across province.

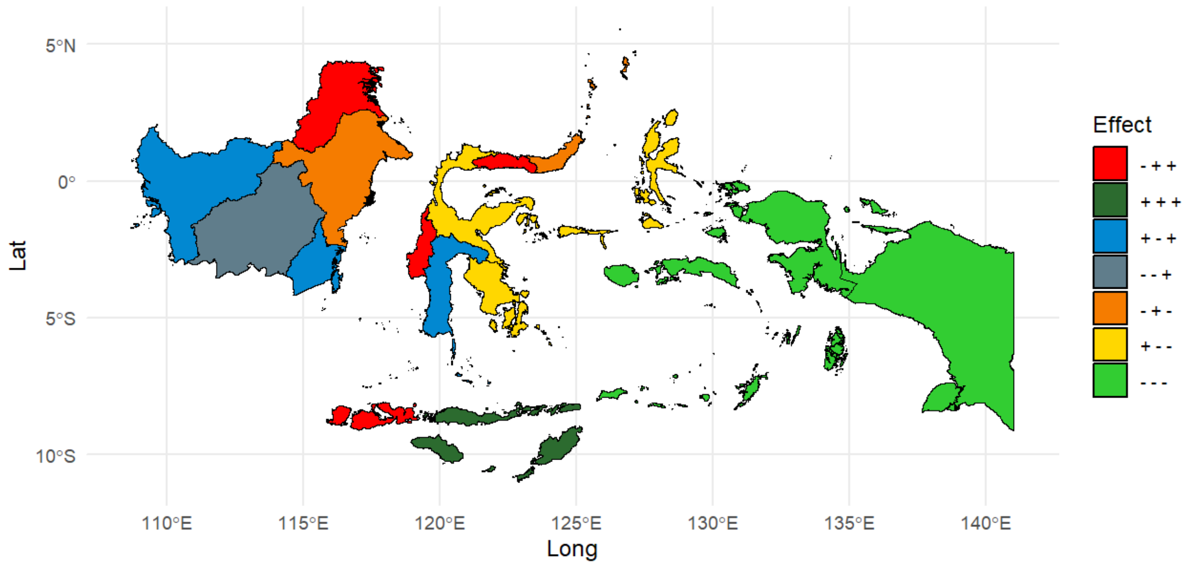

Figure 6. The Effect of X_2 on the Poverty Severity Index
(*Generated using RStudio*)

As illustrated in Fig. 6, the estimated effect of X_2 on the Poverty Severity Index also follows a three-segment spline structure across province. Compared with X_1(see Fig. 5) and X_3 (see Fig. 6), the spatial categorization of X_2 appears more diverse, as indicated by a wider dispersion of effect categories across provinces. This diversity suggests that the influence of education on poverty severity is highly heterogeneous and context-dependent. For instance, in provinces such as Maluku, which appears in light green, the estimated effect of X_2 on the Poverty Severity Index is strongly negative across most segments. In contrast, several other provinces display mixed or even opposing segmental effects. It suggests that the benefits of education are not uniformly realized across regions due to structural disparities. Fig. 7 presents the spatial distribution of the estimated effect of X_3 on the Poverty Severity Index. The resulting spatial pattern appears relatively smoother and more homogeneous across provinces compared to X_1 and X_2 which indicates that the relationship between limited access to healthcare and poverty severity is more consistent across regions.

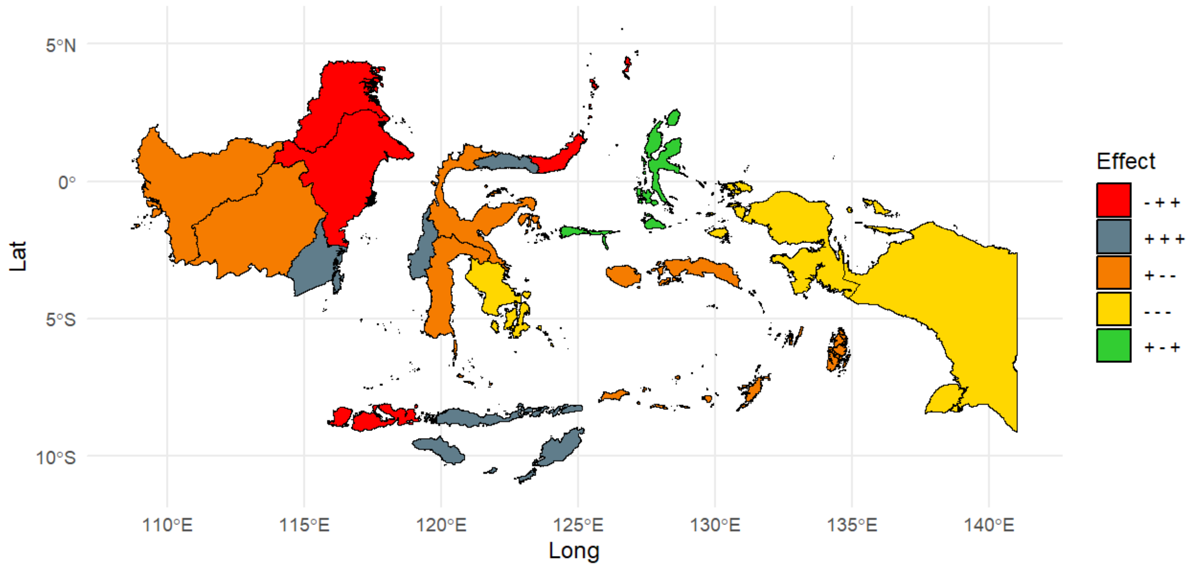

Figure 7. The Effect of X_3 on the Poverty Severity Index
(*Generated using RStudio*)

Based on the figures above, each predictor variable shows a distinct influence on the response variable, namely the Poverty Severity Index. The model produces varied estimation results for each province, which indicates that the two knot spline truncated panel data model is capable of capturing the dynamics and uniqueness of each province. This is reflected in the province-specific estimations generated by the model.

In poverty-related research, particularly in Indonesia, nonparametric spline regression models have demonstrated superior capability in capturing the complex and dynamic relationship between predictor variables and poverty indicators. For instance, a study [48] utilized truncated spline regression with longitudinal data to model rural poverty, unemployment, and agricultural sector growth in Indonesia. This approach effectively identified nonlinear relationships and both temporal and individual heterogeneity across provinces and achieved the lowest GCV for the 3-knot points model. Similarly, a study [49] applied nonparametric truncated spline regression to model the poverty gap index in Bengkulu Province using panel data. This study found that this model adeptly captured regional variations and temporal changes in poverty gap dynamics and achieved excellent value R^2 of 99.89%. These studies showed that the nonparametric spline truncated regression for panel data can accurately capture both regional and temporal variations in poverty indicators.

In the other hand, studies on heterogeneity in predictor effects further support the need for models that consider spatial and temporal differences regarding poverty indicators. A study [50] applied dynamic panel data to analyze poverty across Indonesia and found that the impact of determinants varied between islands, with geographic location and access to education and health facilities affecting poverty differently in each region. Likewise, there is a study analyzing factors affecting poverty in Papua Island from 2017 to 2020 using a Geographically Weighted Panel Regression (GWPR) model revealed clear spatial heterogeneity [51]. Variables such as school year expectancy, life expectancy, and consumption per capita affected poverty differently across districts.

These findings, along with ours, collectively highlight that poverty dynamics in Indonesia exhibit significant spatial and temporal heterogeneity. They underscore the need for policy interventions that are tailored to the specific conditions of each region. By considering spatial differences in poverty determinants, policymakers can allocate resources more effectively, target high-need areas, and design programs that address the unique challenges faced by different communities.

4. CONCLUSION

The parametric Fixed Effect Model (FEM) produced a within R^2 of 36.9% and an MSE of 0.00912, with evidence of heteroskedasticity indicates certain limitations in capturing complex provincial dynamics. In parallel, the nonparametric truncated spline model, selected based on the minimum GCV criterion, provides a more flexible representation of the data and achieved a high in-sample fit (R^2 = 99.875%) and low MSE (0.0004378). However, these results are specific to the analyzed dataset and should not be interpreted as indicating the general superiority of one model over the other, given their differing levels of complexity. Instead, both approaches offer complementary insights, with the FEM providing a parsimonious global structure and the spline model capturing more detailed province-specific patterns. These findings have important policy implications that suggest intervention to the poverty severity should be tailored to the specific economic, educational, and basic healthcare needs of each region. Future research should address several limitations of this study. The short time period (2020–2024) limits the ability to capture long-term dynamics, so extending the observation window is recommended. Additionally, out-of-sample validation is needed to assess predictive performance. Incorporating additional predictors and exploring alternative modeling approaches such as semi-parametric or other nonparametric panel model may also help evaluate the robustness of the findings.

Author Contributions

Dita Amelia: Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing-review and editing. Suliyanto: Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing-review and editing. Najwa Khoir Aldawiyah: Data curation, Formal analysis, Investigation, Software, Writing-Original draft. Kimberly Maserati Siagian: Investigation, Visualization, Writing-Original draft. Nadinta Kasih Amalia: Formal Analysis, Visualization, Writing-Original Draft. Nadya Lovita Hana: Formal Analysis, Investigation, Writing-Original Draft.

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Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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