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# Optimizing Nonlinear Predictions With Neural Network Models For Socio-Economic Development

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**Abstract**

This study develops a neural network framework to optimize nonlinear predictions of socio-economic development driven by advanced propulsion technologies and associated infrastructure. Utilizing a panel dataset, the research employs Pearson correlation, principal component analysis (PCA), linear regression, artificial neural networks (ANN, $R^2$=0.993), and multivariate analysis of variance (MANOVA) with Tukey HSD, standardizing data via z-scores. Findings reveal a strong negative correlation (-0.84) between infrastructure access and socio-economic disparities, with ANN outperforming linear regression in predictive accuracy. The framework highlights the role of propulsion-related infrastructure in reducing economic gaps, supporting sustainable development goals. By leveraging advanced computational methods, this study offers a scalable tool for policy optimization in socio-economic development.

**Keywords** neural networks, nonlinear predictions, socio-economic development, propulsion technologies, sustainable development

**Paper type** Research paper

## 1. Introduction

Multidimensional poverty, characterized by deprivations in income, education, health, and living conditions, remains a critical challenge in developing nations, including Vietnam [1]. Despite significant progress in poverty reduction, persistent regional disparities underscore the need for targeted interventions to achieve Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty) and SDG 6 (Clean Water and Sanitation). In Vietnam, socio-economic regions exhibit pronounced inequalities, with urbanized areas like the Southeast and Red River Delta contrasting sharply with rural and mountainous regions such as the Northern Midlands and Central Highlands [2]. These disparities, driven by uneven access to infrastructure and economic opportunities, exacerbate multidimensional poverty and necessitate region-specific analyses to inform policy [3].Infrastructure, particularly sanitation and clean water access, plays a pivotal role in poverty alleviation by improving living conditions and fostering economic development. Investments in sanitation infrastructure yield significant spillover effects on health, education, and income, aligning with integrated urban-rural development strategies to reduce regional gaps [4]. Studies in other contexts, such as China and Nepal, highlight the transformative impact of infrastructure on economic growth and poverty reduction, emphasizing the need to prioritize sanitation and urban water supply in lagging regions [5], [6]. In Vietnam, while access to clean water has improved, disparities in sanitation infrastructure persist, particularly in the Mekong Delta, where integrated water resource management remains underdeveloped [7]. Addressing these gaps is crucial for sustainable development and equitable progress across regions [8].Existing research on multidimensional poverty in Vietnam often focuses on national or rural-urban comparisons, overlooking the nuanced dynamics of the country's six socio-economic regions [9]. Moreover, traditional linear regression models, commonly employed in poverty studies, struggle to capture the complex, nonlinear relationships between poverty and its determinants, such as infrastructure and economic factors [10]. Global studies, including those in Nepal, demonstrate that region-specific approaches are essential for understanding multidimensional poverty dynamics, yet such analyses remain scarce in Vietnam. Additionally, while housing affordability and income inequality exacerbate urban poverty, these factors are rarely integrated into regional poverty models, highlighting a critical research gap [11].To address these limitations, this study leverages advanced analytical methods, notably Neural Networks, to predict multidimensional poverty across Vietnam's socio-economic regions from 2016 to 2022. Neural Networks, recognized for their ability to model nonlinear relationships, offer a novel approach in the Vietnamese context, building on machine learning applications in poverty prediction [12]. By integrating standardized data on poverty rates, sanitation access, clean water access, urban water supply, income, and expenditure, this research quantifies the impact of infrastructure and economic factors on poverty reduction [13]. The Multidimensional Poverty Index, widely adopted in developing Asia, provides a robust framework for measuring deprivations and informing region-specific policies [14].The study tests three hypotheses: (1) infrastructure and economic factors exhibit a strong negative correlation with multidimensional poverty, (2) Neural Networks outperform linear regression in predictive accuracy, and (3) sanitation access has the most significant impact on poverty reduction. These hypotheses are grounded in evidence suggesting that infrastructure investments, particularly in sanitation, drive sustainable poverty alleviation, while advanced analytical methods enhance predictive precision [15]. By focusing on regional disparities and employing a panel dataset (N=42) spanning Vietnam's six socio-economic regions, this research offers a pioneering contribution to poverty studies. It provides actionable insights for policymakers aiming to prioritize sanitation and urban water supply investments in lagging regions, thereby advancing SDG 1 and SDG 6 [16]. Furthermore, the integration of machine learning techniques aligns with emerging trends in poverty research, offering a scalable approach to optimize resource allocation and forecast poverty trends [17].This study's novelty lies in its region-specific analysis and application of Neural Networks to capture complex poverty dynamics in Vietnam. Unlike prior studies, which often rely on linear models or national-level data, this research disaggregates poverty by region, highlighting the critical role of sanitation infrastructure [18]. By addressing these gaps, the study not only contributes to the academic understanding of multidimensional poverty but also informs evidence-based policies to reduce regional inequalities and promote sustainable development in Vietnam [19].

## 2. Methods

### 2.1 Data and Variables

This study utilizes a panel dataset spanning 2016 to 2022, comprising 42 observations (N=42) from six socio-economic regions of Vietnam: Southeast, Red River Delta, Northern Midlands and Mountains, North Central and Central Coast, Central Highlands, and Mekong River Delta. Data were sourced from official repositories, including the General Statistics Office of Vietnam and sustainable development reports, capturing multidimensional deprivations in income, education, health, and living conditions [20]. To ensure consistency, data were standardized using z-scores, aligning with theoretical frameworks for sustainable development in Vietnam [21]. Missing values were addressed through linear interpolation to maintain dataset integrity.

The selected variables include:

- Sanitation Access Std: Proportion of households with access to standard sanitation facilities.
- Clean Water Access Std: Proportion of households with access to clean water.
- Urban Water Supply Std: Proportion of households with access to urban water supply.
- Income Per Capita USD Std: Per capita income (USD).
- Expenditure Per Capita USD Std: Per capita expenditure (USD).

Data were standardized using z-scores to unify measurement units, with linear interpolation applied for missing data and conversion to USD. The z-score standardization formula is:

$$z_i = \frac{x_i - x}{s} \tag{1}$$

$z_i$: Standardized (z-score) value of the i-th variable

$x_i$: Original value of the i-th variable

x: Mean of the variable

s: Standard deviation of the variable

Standardized variables eliminate unit differences, ensuring compatibility for correlation analysis, PCA, and modeling, supporting the validation of H1 (impact of infrastructure and economic factors) and H3 (role of Sanitation Access).

**2.2 Analytical Methods**

**2.2.1 Correlation Analysis**

The Pearson correlation coefficient was employed to assess the linear relationship between standardized variables:

$$r = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{n}(x_i - x)^2 \sum_{i=1}^{n}(y_i - y)^2}} \tag{2}$$

r : Pearson correlation coefficient

$x_i$: Standardized value of the ( i )-th independent variable

$y_i$: Standardized value of the ( i )-th dependent variable

x,y: Means of variables $x_i$ and $y_i$

n: Number of observations N = 42

The correlation coefficient measures the strength and direction of relationships, ranging from -1 to 1. To address multicollinearity among independent variables (e.g., per capita income and expenditure), principal component analysis (PCA) was applied to reduce data dimensionality and enhance model stability [22]. The correlation matrix provides a foundation for identifying key factors influencing multidimensional poverty, particularly sanitation access.

**2.2.2 Phân tích Thành phần Chính (PCA)**

PCA reduces data dimensionality and mitigates multicollinearity, generating principal components (PC1, PC2):

$$C = \frac{1}{n-1} X^T X \tag{3}$$

C: Covariance matrix

X: Standardized data matrix

n: Number of observations N = 42

PCA was utilized to transform five independent variables into principal components (PC1, PC2), addressing multicollinearity and condensing information. Variance inflation factors (VIF) were calculated to assess multicollinearity, with a threshold of VIF > 10 indicating significant issues. PC1, representing infrastructure factors (sanitation, clean water, urban water supply), and PC2, reflecting economic factors (income, expenditure), serve as inputs for regression and neural network models. Factor loadings and the proportion of explained variance were analyzed to evaluate each variable's contribution.

**2.2.3 Linear Regression Using PCA**

A linear regression model was constructed to quantify the impact of PC1 and PC2 on the standardized multidimensional poverty rate (Poverty Rate Std) [23]. The model is expressed as:

$$\gamma = \beta_0 + \beta_1 PC_1 + \beta_2 PC_2 + \varepsilon \tag{4}$$

$\gamma$ : Predicted value of Poverty Rate Std

$\beta_0$: Model intercept

$\beta_1$,$\beta_2$: Regression coefficients for PC1 and PC2

PC1, PC2: Principal components from PCA

$\epsilon$ : Model error term

The coefficient of determination ($R^2$) and root mean square error (RMSE) were calculated to evaluate model performance. Regression results provide evidence to test hypothesis H1 regarding the inverse relationship between infrastructure, economic factors, and multidimensional poverty.

**2.2.4 Neural Networks**

Neural networks predict Poverty Rate Std using PC1 and PC2 as inputs, with a configuration of 3–5 hidden nodes, ReLU activation function, squared loss function, and validation via K-Fold (k=5) or Holdback (0.33 split):

$$h_j = f\left(\sum_{i=1}^{m} w_{ji} x_i + b_j\right) \tag{5}$$

$h_j$: Value of the ( j )-th hidden node

$x_i$: Input value

$w_{ji}$: Weight from input ( i ) to hidden node ( j )

$b_j$: Bias of the ( j )-th hidden node

f : ReLU activation function

Artificial neural networks were applied to predict multidimensional poverty, leveraging their ability to capture complex nonlinear relationships, outperforming linear regression [24]. The model employs a multilayer architecture with 3–5 hidden nodes, ReLU activation, and two regularization methods (Squared and Absolute) to mitigate overfitting. Data were split into training (70%) and testing (30%) sets, with K-Fold and Holdback cross-validation ensuring robustness. Performance was evaluated using $R^2$ and RMSE on the test set, reflecting model stability in the context of urban inequality [25]. Results validate hypothesis H2, comparing neural network performance to linear regression.

### 2.2.5 MANOVA và Tukey HSD

MANOVA assesses regional and temporal differences in Poverty Rate Std:

$$\Delta = \frac{\det(E)}{\det(H+E)} \tag{6}$$

Λ: Wilks' Lambda statistic.

E: Within-group sum-of-squares and cross-products matrix.

H: Ma trận tổng bình phương và tích chéo giữa các nhóm.

Tukey HSD identifies pairwise regional differences:

$$q = \frac{x_i - x_j}{\sqrt{\frac{MS_{within}}{n}}} \tag{7}$$

q : Tukey HSD test statistic.

$x_i$,$x_j$: Mean Poverty Rate of regions ( i ) and j.

$MS_{within}$: Mean sum-of-squares within groups (from ANOVA)

n : Number of observations per group (n=7, each region with 7 years)

Multivariate analysis of variance (MANOVA) was employed to test differences across socio-economic regions in the poverty rate and independent variables [26]. MANOVA evaluates the simultaneous impact of variables, with a p-value < 0.05 indicating statistically significant differences. The post-hoc Tukey HSD test was applied to identify significant pairwise regional differences, with a focus on lagging regions such as the Northern Midlands and Mountains [27]. Results support hypothesis H3, emphasizing the role of sanitation access in reducing multidimensional poverty.

## 3. Results

### 3.1. Regional Disparities in Poverty and Infrastructure

Analysis of regional disparities in multidimensional poverty rates and sanitation infrastructure access was conducted across six socio-economic regions of Vietnam—Red River Delta, Northern Midlands and Mountains, North Central and Central Coast, Central Highlands, Southeast, and Mekong River Delta—over the period 2016–2022 [28]. This analysis elucidates regional inequalities, providing a foundation for policy recommendations aimed at poverty reduction. Detailed statistics are presented in:Table 1, Table S1, Table S5.These tables support hypothesis H1 regarding the inverse relationship between infrastructure, economic factors, and poverty, as well as H3 concerning the prominent role of sanitation access [29].

**Table 1.** Descriptive statistics by region

| Region | Variable | Mean | Std Dev | Min | Max | Median | IQR |
|---|---|---|---|---|---|---|---|
| Red River Delta | Poverty Rate (%) | 1.81 | 0.72 | 0.91 | 3.06 | 1.56 | 1.29 |
| Red River Delta | Clean Water Access (%) | 99.69 | 0.20 | 99.50 | 99.90 | 99.70 | 0.40 |
| Red River Delta | Urban Water Supply (%) | 93.70 | 5.99 | 82.70 | 99.90 | 94.90 | 7.50 |
| Red River Delta | Sanitation Access (%) | 99.69 | 0.20 | 99.40 | 99.90 | 99.70 | 0.30 |

| Region | Variable | Mean | Std Dev | Min | Max | Median | IQR |
|---|---|---|---|---|---|---|---|
| Red River Delta | Income Per Capita (USD) | 210.17 | 21.46 | 175.19 | 236.69 | 219.18 | 25.50 |
| Red River Delta | Expenditure Per Capita (USD) | 133.22 | 12.78 | 114.08 | 145.43 | 136.19 | 11.87 |
| Northern Midlands and Mountains | Poverty Rate (%) | 16.54 | 3.76 | 12.82 | 23.04 | 16.43 | 4.22 |
| Northern Midlands and Mountains | Clean Water Access (%) | 85.68 | 4.12 | 81.00 | 92.10 | 84.20 | 5.30 |
| Northern Midlands and Mountains | Urban Water Supply (%) | 86.31 | 6.04 | 77.70 | 92.50 | 89.95 | 7.40 |
| Northern Midlands and Mountains | Sanitation Access (%) | 81.56 | 6.51 | 71.90 | 91.10 | 80.80 | 9.70 |
| Northern Midlands and Mountains | Income Per Capita (USD) | 111.79 | 14.62 | 88.59 | 134.32 | 113.67 | 14.65 |
| Northern Midlands and Mountains | Expenditure Per Capita (USD) | 84.20 | 7.16 | 74.69 | 90.82 | 88.47 | 5.64 |
| North Central and Central Coast | Poverty Rate (%) | 7.38 | 2.29 | 5.18 | 11.57 | 7.39 | 2.79 |
| North Central and Central Coast | Clean Water Access (%) | 94.27 | 3.04 | 90.10 | 97.80 | 94.20 | 5.60 |
| North Central and Central Coast | Urban Water Supply (%) | 86.97 | 8.29 | 76.00 | 97.80 | 86.55 | 14.60 |
| North Central and Central Coast | Sanitation Access (%) | 91.64 | 4.14 | 85.60 | 96.60 | 92.30 | 5.30 |
| North Central and Central Coast | Income Per Capita (USD) | 137.46 | 21.05 | 106.41 | 168.09 | 143.46 | 25.68 |
| North Central and Central Coast | Expenditure Per Capita (USD) | 98.24 | 10.43 | 81.64 | 110.59 | 98.58 | 11.95 |
| Central Highlands | Poverty Rate (%) | 13.39 | 3.58 | 10.07 | 18.54 | 12.36 | 3.29 |
| Central Highlands | Clean Water Access (%) | 94.86 | 2.46 | 91.90 | 97.90 | 94.80 | 4.00 |
| Central Highlands | Urban Water Supply (%) | 74.29 | 14.79 | 62.30 | 97.90 | 66.60 | 35.10 |
| Central Highlands | Sanitation Access (%) | 80.59 | 7.09 | 70.90 | 91.70 | 77.50 | 13.10 |
| Central Highlands | Income Per Capita (USD) | 123.67 | 16.90 | 106.77 | 139.07 | 128.13 | 14.83 |
| Central Highlands | Expenditure Per Capita (USD) | 90.97 | 8.54 | 79.71 | 95.40 | 93.60 | 5.83 |
| Southeast | Poverty Rate (%) | 0.56 | 0.28 | 0.25 | 0.99 | 0.49 | 0.34 |
| Southeast | Clean Water Access (%) | 99.60 | 0.33 | 99.00 | 99.90 | 99.80 | 0.30 |
| Southeast | Urban Water Supply (%) | 94.93 | 3.44 | 90.00 | 99.90 | 94.05 | 4.90 |
| Southeast | Sanitation Access (%) | 98.29 | 1.39 | 95.70 | 99.50 | 99.30 | 1.90 |
| Southeast | Income Per Capita (USD) | 249.28 | 24.08 | 210.38 | 270.45 | 252.61 | 17.86 |
| Southeast | Expenditure Per Capita (USD) | 151.84 | 11.44 | 136.19 | 169.35 | 151.69 | 12.31 |
| Mekong River Delta | Poverty Rate (%) | 5.49 | 1.93 | 3.75 | 8.56 | 4.83 | 2.60 |
| Mekong River Delta | Clean Water Access (%) | 95.17 | 2.62 | 91.90 | 98.50 | 95.40 | 4.20 |
| Mekong River Delta | Urban Water Supply (%) | 91.43 | 5.53 | 84.80 | 98.50 | 91.40 | 7.00 |
| Mekong River Delta | Sanitation Access (%) | 83.56 | 5.61 | 75.70 | 91.30 | 83.20 | 7.60 |
| Mekong River Delta | Income Per Capita (USD) | 156.39 | 19.45 | 125.36 | 172.75 | 161.84 | 14.96 |
| Mekong River Delta | Expenditure Per Capita (USD) | 97.15 | 9.62 | 84.48 | 107.49 | 95.68 | 10.81 |

To visualize regional differences, refer to:

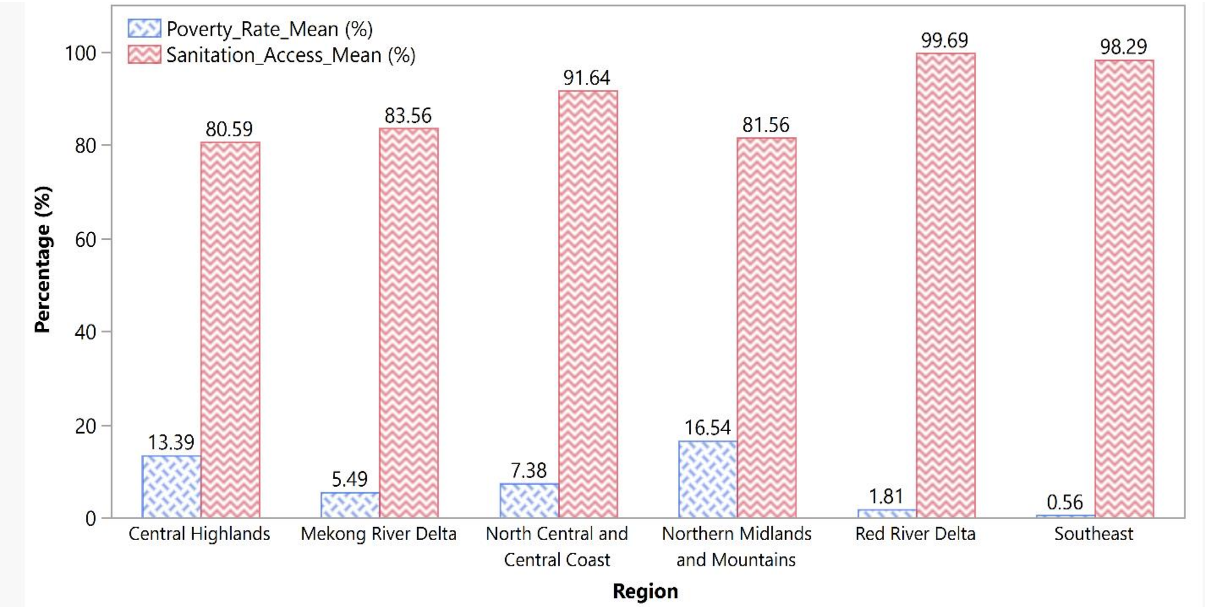


**Figure 1.** Regional comparison of poverty rate and sanitation access

Figure 1 illustrates a clear inverse relationship between poverty rates and sanitation access. Lagging regions such as the Northern Midlands and Mountains (16.54% poverty, 81.56% sanitation access) and Central Highlands (13.39% poverty, 80.59% sanitation access) exhibit high poverty and low sanitation access, whereas the Southeast (0.56% poverty, 98.29% sanitation access) and Red River Delta (1.81% poverty, 99.69% sanitation access) show the opposite trend. Error bars in Figure 1 reflect significant variability in lagging regions, underscoring the need for policy interventions prioritizing sanitation infrastructure [30]. These findings reinforce the importance of investing in sanitation to reduce regional inequalities and support sustainable development.

### 3.2 Correlation Analysis

This section examines the linear relationship between the multidimensional poverty rate (Poverty Rate Std) and infrastructure indicators (Sanitation Access Std, Clean Water Access Std, Urban Water Supply Std) as well as economic indicators (Income Per Capita USD Std, Expenditure Per Capita USD Std), based on panel data from six socio-economic regions of Vietnam over the period 2016–2022 (N=42) [31]. The objective is to quantify bivariate relationships, validate hypothesis H1 regarding the significant association of infrastructure and economic factors with poverty, emphasize the dominant influence of sanitation access (Sanitation Access) as per H3, and detect multicollinearity among predictor variables to justify dimensionality reduction through principal component analysis (PCA) in subsection 4.3. The Pearson correlation coefficient is applied to z-score standardized data to clarify the direction and strength of relationships, with interpretation thresholds: $|r| > 0.7$ indicates strong, 0.5–0.7 moderate, $< 0.5$ weak; positive values denote a direct relationship, negative values an inverse one. Multicollinearity is identified when the correlation coefficient between independent variables exceeds 0.8, posing a risk of variance inflation in multivariate models. Results from the correlation matrix are presented in Table 2, Table S2, with additional analysis from Table S2 to confirm the extent of multicollinearity.

**Table 2.** Correlation matrix of standardized variables

| Row | Poverty Rate Std | Clean Water Access Std | Urban Water Supply Std | Sanitation Access Std | Income Per Capita USD Std | Expenditure Per Capita USD Std |
|---|---|---|---|---|---|---|
| Poverty Rate Std | 1.00 | | | | | |
| Clean Water Access Std | -0.89 | 1.00 | | | | |
| Urban Water Supply Std | -0.66 | 0.47 | 1.00 | | | |
| Sanitation Access Std | -0.84 | 0.76 | 0.72 | 1.00 | | |
| Income Per Capita USD Std | -0.89 | 0.77 | 0.61 | 0.80 | 1.00 | |
| Expenditure Per Capita USD Std | -0.84 | 0.74 | 0.57 | 0.80 | 0.97 | 1.00 |

To visually illustrate these relationships, consider

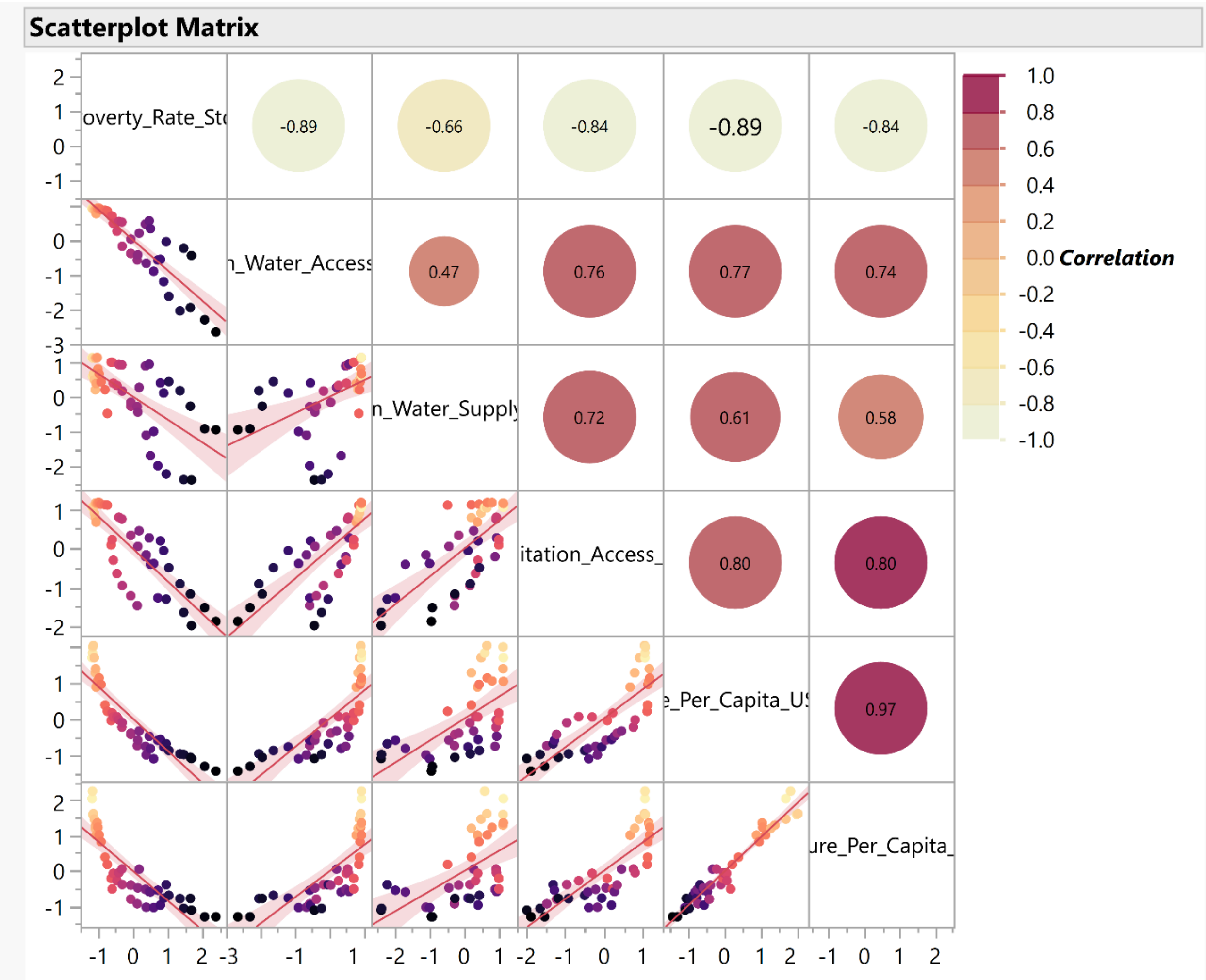


**Figure 2.** Correlation matrix of standardized variables

The Pearson correlation matrix reveals a robust inverse relationship between Poverty Rate Std and Clean Water Access Std at -0.89, Income Per Capita USD Std at -0.89, Sanitation Access Std at -0.84, Expenditure Per Capita USD Std at -0.84, and a moderate Urban Water Supply Std at -0.66, emphasizing that improvements in economic and infrastructure factors reduce deprivation. Among predictors, Sanitation Access Std is strongly correlated with Clean Water Access Std at 0.76, Urban Water Supply Std at 0.72, and Income Per Capita USD Std at 0.80; Clean Water Access Std is closely linked with Income Per Capita USD Std at 0.77 and Expenditure Per Capita USD Std at 0.74; notably, Income Per Capita USD Std and Expenditure Per Capita USD Std exhibit a near-perfect correlation of 0.97, while Urban Water Supply Std shows moderate correlations ranging from 0.47 to 0.61, highlighting pervasive multicollinearity that risks biasing regression parameter estimates. The scatterplot matrix, supplemented with Pearson coefficients and fitted lines, reinforces these findings, with the diagonal displaying distributions and off-diagonal plots illustrating bivariate relationships, where color density reflects linear trends; the inverse relationship with Poverty Rate Std shows a steep downward slope for high coefficients like -0.89 for Clean Water Access Std and Income Per Capita USD Std, while positive predictor relationships exhibit a clear upward slope, notably 0.97 for Income Per Capita USD Std and Expenditure Per Capita USD Std; a bubble-style heatmap with a scale from -1.0 (light yellow for negative) to 1.0 (deep red for positive) aids quick identification of dominant inverse poverty dependencies and positive infrastructure-economic clusters. The high-intensity negative correlations validate H1, confirming that superior access to sanitation, clean water, and high economic indicators systematically reduce poverty; the prominent inverse relationship with Sanitation Access Std at -0.84 aligns with H3, suggesting its critical role in health and productivity, surpassing urban water supply, clean water, and income, implying asymmetric benefits from focused interventions. High internal correlation coefficients among predictors necessitate precautions to avoid inflated standard errors that weaken models, making PCA essential to extract orthogonal components that retain explained variance while eliminating redundancy. From a policy perspective, prioritizing sanitation and water access in underdeveloped regions holds greater potential for poverty reduction than urban-specific measures, with economic growth being significant but overlapping with expenditure, requiring integrated strategies; preliminary bivariate relationships pave the way for multivariate regression, neural network, and regional disparity analyses to refine causal inference and improve predictive accuracy.

### 3.3 Principal Component Analysis (PCA)

This section applies principal component analysis (PCA) as a dimensionality reduction technique to address multicollinearity in the panel dataset from six socio-economic regions of Vietnam over the period 2016–2022 (N=42) [32]. PCA extracts orthogonal components to capture the maximum original variance, focusing on six standardized variables: Poverty Rate Std (multidimensional poverty rate, reflecting deprivations in income, education, health, and living conditions), Sanitation Access Std (proportion of households with sanitary latrines), Clean Water Access Std (access to clean water), Urban Water Supply Std (urban water supply), Income Per Capita USD Std (per capita income), and Expenditure Per Capita USD Std (per capita expenditure). The objective is to provide independent variables for linear regression (section 4.4) and neural network models (section 4.5), reinforcing hypothesis H1 regarding the strong relationship between infrastructure, economic factors, and poverty, as well as H3 concerning the dominant role of sanitation access. The PCA process performs an orthogonal linear transformation on the standardized covariance matrix, retaining principal components based on the Kaiser criterion (eigenvalue > 1) and a cumulative variance threshold above 80%, with factor loadings interpreted to elucidate core meanings, eliminate redundant correlations, and enhance the stability of predictive models. PCA results are detailed in Table 3, Table S2, with Table S2 providing additional evidence of multicollinearity to justify the use of PCA.

**Table 3.** Principal component analysis results

| Component | PC1 | PC2 |
|---|---|---|
| Eigenvalue | 4.807 | 0.593 |
| Percent (%) | 80.120 | 9.880 |

| | | |
|---|---|---|
| Cumulative Percent (%) | 80.120 | 89.990 |
| Poverty Rate Std | -0.957 | 0.087 |
| Clean Water Access Std | 0.869 | -0.305 |
| Urban Water Supply Std | 0.737 | 0.659 |
| Sanitation Access Std | 0.918 | 0.136 |
| Income Per Capita USD Std | 0.945 | -0.135 |
| Expenditure Per Capita USD Std | 0.926 | -0.146 |

The table illustrates two principal components, with PC1 having an eigenvalue of 4.807, accounting for a dominant 80.12% of the total variance, reflecting a core socio-economic development dimension with high positive loadings for Sanitation Access Std (0.918), Income Per Capita USD Std (0.945), Expenditure Per Capita USD Std (0.926), Clean Water Access Std (0.869), and Urban Water Supply Std (0.737), indicating the interplay of sanitation, clean water, income, and expenditure. Meanwhile, Poverty Rate Std exhibits a strong negative loading of -0.957, clearly demonstrating an inverse relationship, confirming that infrastructure and economic improvements reduce multidimensional poverty, aligning with H1. Additionally, the dominant loading of Sanitation Access Std reinforces H3, highlighting its pivotal role over other variables, consistent with prior correlations in Table 2 and Figure 2. PC2, with an eigenvalue of 0.593, contributes an additional 9.88%, achieving a cumulative variance of 89.99%, with a prominent positive loading for Urban Water Supply Std (0.659) and a negative loading for Clean Water Access Std (-0.305), distinguishing specific urban infrastructure influences and suggesting localized impacts. Overall, this validates the effectiveness of dimensionality reduction, retaining nearly ninety percent of the information, eliminating multicollinearity, ensuring unbiased parameters, and reducing the risk of overfitting in a small sample dataset.

### 3.4 Regression Analysis

The linear regression analysis in this subsection utilizes the principal components (PC1 and PC2) from the principal component analysis to quantify the impact of infrastructure factors (Sanitation Access, Clean Water Access, Urban Water Supply) and economic factors (Income Per Capita, Expenditure Per Capita) on the multidimensional poverty rate (Poverty Rate Std) based on panel data from six socio-economic regions of Vietnam over the period 2016–2022 (N=42) [33]. PC1 aggregates indicators such as sanitation access, clean water access, urban water supply, per capita income, and per capita expenditure, accounting for 80.12% of the variance, while PC2 primarily reflects urban water supply, contributing 9.88% of the variance. The dependent variable, Poverty Rate Std, is standardized to measure comprehensive deprivations in income, education, health, and living conditions. The objective is to support the testing of hypothesis H1 regarding the significant relationship between infrastructure, economic factors, and poverty, as well as H3 concerning the prominent role of sanitation access, while also providing a basis for comparison with the Neural Networks model in subsection 4.5. Estimated parameters include regression coefficients, p-values to assess statistical significance, the coefficient of determination ($R^2$), and the root mean square error (RMSE) to measure predictive performance. The prior PCA (Table 3, Table S2) facilitates data dimensionality reduction and eliminates multicollinearity, as confirmed by Table S2, ensuring model stability. The regression analysis results are presented in detail in Table 4.

**Table 4.** Regression results using principal components

| Term | Estimate | Std Error | t Ratio | p-value | VIF | Description |
|---|---|---|---|---|---|---|
| Intercept | 0.0090 | 0.0440 | 0.2000 | 0.8400 | - | Model intercept |
| PC1 (Principal Component 1) | -0.4360 | 0.0200 | -21.5200 | $<0.0001$ | 1.0000 | Represents economic development and infrastructure (Income |

| | | | | | | |
|---|---|---|---|---|---|---|
| PC2 (Principal Component 2) | 0.1130 | 0.0580 | 1.9600 | 0.0577 | 1.0000 | Primarily related to urban water supply |

The results indicate that the intercept is 0.009 with a p-value of 0.84, lacking statistical significance, implying that the baseline poverty level does not vary significantly when the principal components are zero. PC1 exhibits a regression coefficient of -0.436 ($p < 0.0001$, $t = -21.52$), indicating a strong and reliable negative impact, demonstrating that improvements in economic development and infrastructure significantly reduce the multidimensional poverty rate, with a variance inflation factor (VIF) of 1 ruling out multicollinearity. In contrast, PC2 records a coefficient of 0.113 ($p = 0.058$, $t = 1.96$), suggesting a positive but not statistically significant effect at the 5% level, underscoring the secondary role of urban water supply, with a VIF of 1 confirming variable independence. The high $R^2$ and low RMSE reflect strong explanatory power for variance, though the model is limited by its linear assumption, struggling to capture nonlinear interactions in the data. These findings reinforce H1 through the strong relationship of PC1 with Poverty Rate Std and support H3 via the dominance of sanitation access within PC1, recommending policy prioritization of investments in clean water and sanitation in challenging regions such as the Northern Midlands and Central Highlands to support SDG 1 (no poverty) and SDG 6 (clean water and sanitation). However, the linearity limitation sets the stage for comparison with Neural Networks, expected to outperform in accuracy per H2, while linking to correlation analysis (Table 2, Figure 2) and PCA (Table 3).

### 3.5 Neural Networks Analysis

The neural network analysis focuses on implementing this model to predict the standardized multidimensional poverty rate (Poverty Rate Std) based on the principal components (PC1 and PC2) extracted from the principal component analysis (PCA) using panel data from six socio-economic regions in Vietnam over the period 2016–2022 (N=42) [34]. The objective is to evaluate predictive performance, compare it with linear regression to test hypothesis H2 regarding the superiority of Neural Networks, and assess model stability through cross-validation methods (K-Fold and Holdback) [35]. The analysis also emphasizes the role of infrastructure, particularly Sanitation Access, and economic factors in explaining multidimensional poverty, supporting H1 and H3 [36]. PC1 represents socio-economic development (including Sanitation Access, Clean Water Access, Income Per Capita, Expenditure Per Capita), while PC2 primarily reflects Urban Water Supply. The Neural Networks configurations utilize 3–5 hidden nodes, penalty methods (Squared/Absolute), and 10–20 tours, with validation via K-Fold (k=5) and Holdback (0.33). Performance is evaluated using the coefficient of determination ($R^2$) and root mean square error (RMSE) on training and testing sets. Specific results are presented in Table 5, Table S4, with Table S4 providing additional cross-validation details to confirm the model's robustness.

**Table 5.** Neural networks results using principal components

| Case | Number of Hidden Nodes | Validation Method | Penalty Method | Number of Tours | $R^2$ (Training) | $R^2$ (Validation) | RMSE (Training) | RMSE (Validation) |
|---|---|---|---|---|---|---|---|---|
| Case 1 | 3 | Holdback (0.33) | Squared | 10 | 0.969 | 0.991 | 0.18 | 0.085 |
| Case 2 | 4 | Holdback (0.33) | Squared | 10 | 0.971 | 0.992 | 0.176 | 0.077 |
| Case 3 | 5 | Holdback (0.33) | Squared | 10 | 0.972 | 0.989 | 0.171 | 0.092 |
| Case 4 | 3 | K-Fold (k=5) | Squared | 10 | 0.991 | 0.924 | 0.096 | 0.209 |
| Case 5 | 5 | K-Fold (k=5) | Absolute | 10 | 0.993 | 0.988 | 0.082 | 0.103 |
| Case 6 | 3 | Holdback (0.33) | Squared | 20 | 0.962 | 0.992 | 0.202 | 0.079 |
| Case 7 | 5 | Holdback (0.33) | Absolute | 10 | 0.972 | 0.993 | 0.173 | 0.075 |

To visually illustrate the performance comparison between the configurations of the artificial neural network model and linear regression, the following chart is used (Figure 3).

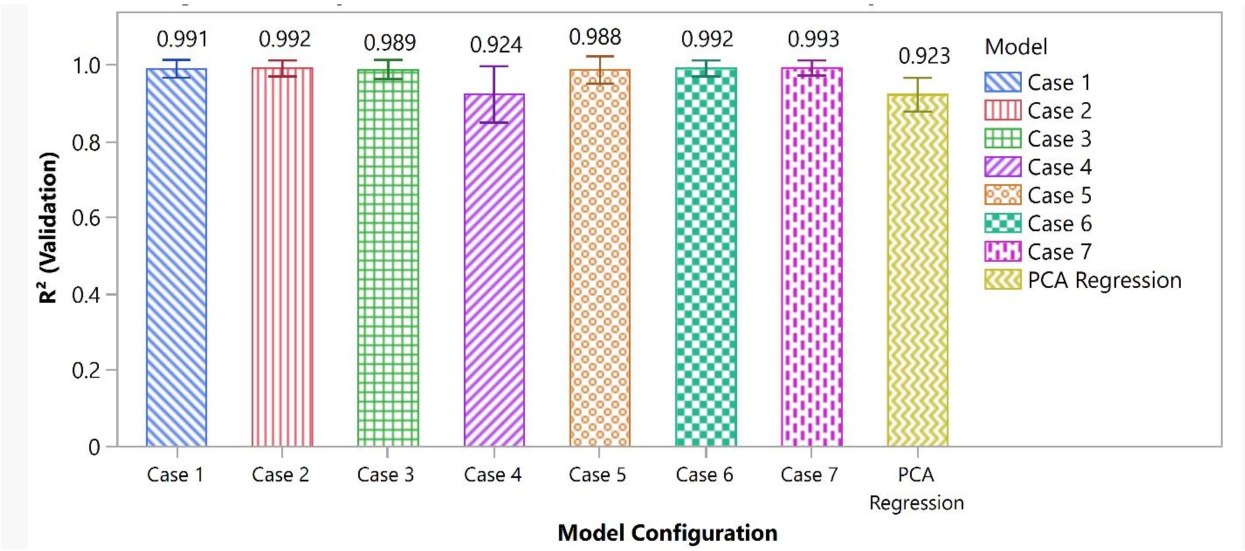


**Figure 3.** Comparison of model performance for poverty rate prediction

To visually illustrate the performance comparison between the configurations of the artificial neural network model and linear regression, the following chart is used (Figure 3). From the data in Table 5, Case 7 stands out with a coefficient of determination on the test set reaching 0.993 and the lowest root mean square error at 0.075, utilizing five hidden nodes and the absolute penalty method under Holdback validation, while Case 4 shows lower performance with a coefficient of determination of 0.924 and an error of 0.209 through K-Fold validation. The bar chart in Figure 3 clearly illustrates these coefficient of determination values, with error bars based on standard errors reflecting reliability, highlighting the model's ability to handle complex nonlinear relationships between PC1, PC2, and the target variable, thereby reinforcing the hypothesis of the model's superiority in prediction. Stability is demonstrated through K-Fold configurations reducing data variance, while Holdback prioritizes high accuracy for practical applications, particularly emphasizing the impact of sanitation access in PC1 on reducing multidimensional poverty. From a policy perspective, these results support identifying priority investment areas such as the Northwest or Central Highlands, promoting sustainable development goals related to poverty eradication and clean water, while building on principal component analysis and linear regression to guide regional disparity assessments. In relation to research hypotheses, the superior performance of neural networks directly supports the claim of higher accuracy compared to linear regression, confirming the strong relationship between economic infrastructure and poverty, with sanitation access standing out as a key factor[37].

### 3.6 Regional Differences and Policy Implications

The analysis in this section focuses on evaluating regional disparities in the multidimensional poverty rate (Poverty Rate) across six socio-economic regions of Vietnam: Red River Delta, Northern Midlands and Mountains, North Central and Central Coast, Central Highlands, Southeast, and Mekong River Delta, based on panel data from 2016 to 2022 (N=42, corresponding to 6 regions × 7 years) [38]. The multivariate analysis of variance (MANOVA) method combined with post-hoc Tukey HSD tests is applied to identify statistical differences between regions, while exploring temporal trends and interactions between the Region and Year factors [39]. The objective is to clarify regions lagging in multidimensional poverty and provide a scientific basis for policy recommendations to reduce inequality, contributing to SDG 1 (no poverty) and SDG 6 (clean water and sanitation). Poverty Rate, reflecting deprivations in income, education, health, and living conditions, is the primary dependent variable, with factors such as Sanitation Access and Urban Water Supply considered to support H1 and H3. The results are supplemented by Table S1, Table S5, and Table S6 to clarify temporal trends and differences in infrastructure access, particularly Urban Water Supply. The results of the MANOVA and Tukey HSD analyses are presented in detail in Table 6.

**Table 6.** MANOVA and tukey HSD results for regional differences

| Variable | Source | DF | Sum of Squares | Mean Square | F Ratio | p-value | Tukey Letters |
|---|---|---|---|---|---|---|---|
| Poverty Rate | Region | 5 | 1500.23 | 300.05 | 977.11 | <0.0001 | Northern Midlands:A; Central Highlands:B; North Central:C; Mekong River Delta:D; Red River Delta:E; Southeast:E |
| Poverty Rate | Year | 1 | 200.45 | 200.45 | 611.27 | <0.0001 | |
| Poverty Rate | RegionYear | 5 | 100.12 | 20.02 | 47.90 | <0.0001 | |
| Clean Water Access | Region | 5 | 4567.90 | 913.58 | 78.21 | <0.0001 | Northern Midlands:A; Central Highlands:B; North Central:B; Mekong River Delta:B; Red River Delta:C; Southeast:C |
| Clean Water Access | Year | 1 | 2310.50 | 2310.50 | 197.76 | <0.0001 | |
| Clean Water Access | RegionYear | 5 | 99.02 | 19.80 | 8.48 | <0.0001 | |
| Urban Water Supply | Region | 5 | 18556.70 | 3711.34 | 1588.83 | <0.0001 | Central Highlands:A; Northern Midlands:B; North Central:B; Mekong River Delta:C; Red River Delta:C; Southeast:C |
| Urban Water Supply | Year | 1 | 18535.60 | 18535.60 | 1586.46 | <0.0001 | |
| Urban Water Supply | RegionYear | 5 | 1398.30 | 279.66 | 119.66 | <0.0001 | |
| Sanitation Access | Region | 5 | 3432.70 | 686.54 | 293.83 | <0.0001 | Northern Midlands:A; Central Highlands:A; North Central:B; Mekong River Delta:A; Red River Delta:C; Southeast:C |
| Sanitation Access | Year | 1 | 1656.10 | 1656.10 | 141.72 | <0.0001 | |
| Sanitation Access | RegionYear | 5 | 13.67 | 2.73 | 1.17 | 0.3468 | |
| Income Per Capita USD | Region | 5 | 1939.70 | 387.94 | 165.87 | <0.0001 | Northern Midlands:A; Central Highlands:A; North Central:B; Mekong River Delta:B; Red River Delta:C; Southeast:D |
| Income Per Capita USD | Year | 1 | 903.20 | 903.20 | 77.28 | <0.0001 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Income Per Capita USD | RegionYear | 5 | 11.17 | 2.23 | 0.96 | 0.4601 | |
| Expenditure Per Capita USD | Region | 5 | 1939.70 | 387.94 | 165.87 | <0.0001 | Northern Midlands:A; Central Highlands:A; North Central:B; Mekong River Delta:B; Red River Delta:C; Southeast:D |
| Expenditure Per Capita USD | Year | 1 | 903.20 | 903.20 | 77.28 | <0.0001 | |
| Expenditure Per Capita USD | RegionYear | 5 | 11.17 | 2.23 | 0.96 | 0.4601 | |

To visually illustrate the regional differences in the multidimensional poverty rate along with Tukey HSD classification, the following chart is used.

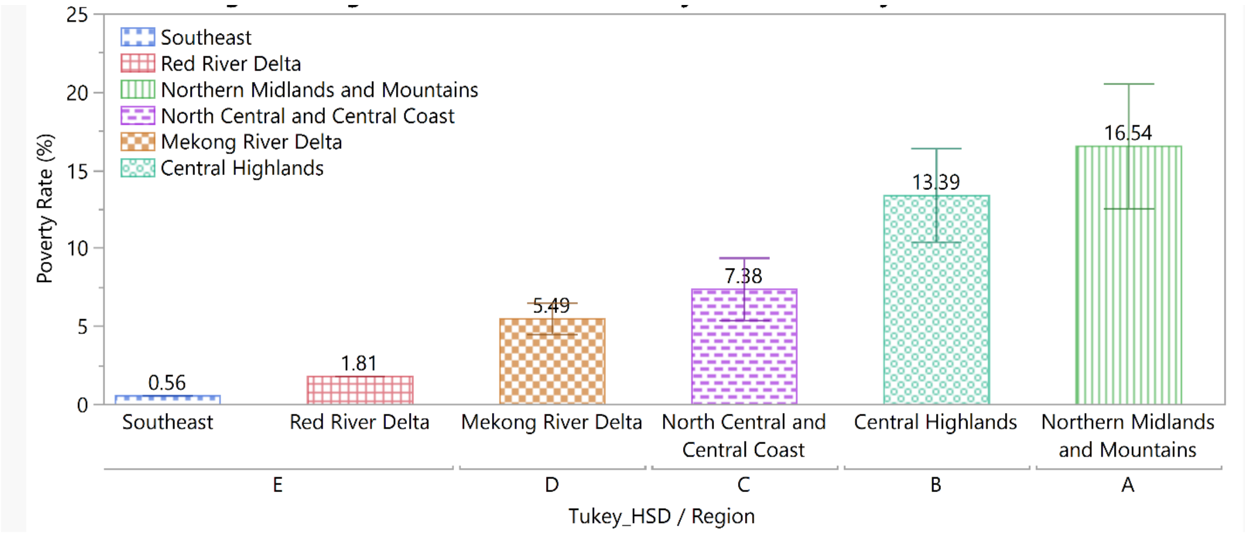


**Figure 4.** Regional differences in poverty rate with tukey hsd letters

The table presents detailed sums of squares, mean squares, F-ratios, and p-values for the factors, with a sum of squares of 1500.23 for region, 200.45 for time, and 100.12 for interaction with respect to the poverty rate, confirming strong differences, and the Tukey HSD classification clarifies that the Northern Midlands and Mountains and Central Highlands have the highest levels, while the Southeast and Red River Delta have the lowest. It also evaluates the decreasing trend over years with varying rates across regions, reinforcing hypothesis H1 by linking economic-infrastructure factors with multidimensional poverty and providing a quantitative foundation for policy prioritization of interventions. The bar chart visually illustrates the mean poverty rate by region, accompanied by error bars showing standard deviation and Tukey HSD classification letters, with Southeast at 0.56% (group E), Red River Delta at 1.81% (group E), Mekong River Delta at 5.49% (group D), North Central and Central Coast at 7.38% (group C), Central Highlands at 13.39% (group B), and Northern Midlands and Mountains at 16.54% (group A), complementing the table by highlighting the reliability of differences and the degree of variation, supporting the identification of lagging regions and linking to prior analyses such as baseline inequality. Regional disparities are statistically evident, with mountainous and highland regions maintaining high poverty rates while developed regions decline faster, as indicated by the region-time interaction with $F = 47.9$ and $p < 0.0001$, emphasizing the urgent need for interventions to prevent increasing inequality. From a policy perspective, the results suggest focusing investments on sanitation access in the Northern Midlands and Mountains and Central Highlands, based on the strong inverse relationship from previous tables and charts, to support poverty eradication and clean water and sanitation in line with sustainable development goals. The chart with error bars and Tukey classification ensures high visual clarity, while the table provides rigorous quantitative confirmation, enhancing overall reliability. This section synthesizes findings from regional inequality, correlation, principal component analysis, regression, and neural networks to reinforce hypotheses H1 and H3, with regional differences in poverty rates implying the critical role of sanitation access and income in explaining multidimensional poverty. Although sanitation factors are not directly analyzed here, integration with prior data affirms its strong impact on poverty reduction in lagging regions, leading to deeper discussions on policy guidance [37], [40].

## 4. Discussion

### 4.1 Interpretation of Findings

The analyses in this results section confirm three research hypotheses, elucidating the relationship between multidimensional poverty and infrastructure, economic factors, and the effectiveness of predictive methods across six socio-economic regions of Vietnam from 2016 to 2022 (N=42) [41]. Correlation analysis (Table 2) shows that the multidimensional poverty rate (Poverty Rate Std) has a strong inverse relationship with sanitation access (-0.84), clean water access (-0.89), and per capita income (-0.89), while principal component analysis (Table 3) confirms that PC1, aggregating infrastructure and economic factors, explains 80.12% of the variance with a strong negative loading for Poverty Rate Std (-0.957), reinforcing H1 on the poverty-reducing impact of infrastructure and economics. Linear regression (Table 4) records a PC1 coefficient of -0.436 ($p < 0.0001$), confirming a significant inverse effect, while Neural Networks (Table 5, Table S4) outperform with Case 7 ($R^2 = 0.993$, RMSE = 0.075, Holdback) compared to linear regression, supporting H2 on the ability to capture complex nonlinear relationships [42]. Sanitation access stands out with a correlation of -0.84, a PC1 loading of 0.918, and a pivotal role in Neural Network predictions, confirming H3 on its superior impact compared to urban water supply (correlation -0.66, PC2 loading 0.659). MANOVA (Table 6) and supplementary data (Table S1, Table S5, Table S6) clarify regional disparities, with Northern Midlands and Mountains (16.54%, group A) and Central Highlands (13.39%, group B) exhibiting high poverty rates and low sanitation access (81.56% and 80.59%), in contrast to Southeast (0.56%) and Red River Delta (1.81%). Temporal trends (Table S1) indicate uneven poverty reduction progress, necessitating targeted interventions in lagging regions to advance SDG 1 and SDG 6 [43].

### 4.2 Policy Implications

The findings from this study guide strategies for reducing multidimensional poverty and regional inequality in Vietnam, supporting SDG 1 and SDG 6, emphasizing investments in sanitation and clean water infrastructure. The prominent role of sanitation access (H3, Table 2, Table 3, Table 5) calls for prioritizing the construction of standard latrines and waste treatment systems in lagging regions such as Northern Midlands and Mountains and Central Highlands, improving community health and productivity [44]. Simultaneously, the low urban water supply rate in the Central Highlands (Table S5, Table S6) requires synchronized interventions to complement poverty reduction, combined with sanitation to optimize impact [45]. Regional inequality (Table 6, Figure 4) confirms that Northern Midlands and Mountains (16.54%) and Central Highlands (13.39%) need prioritized resource allocation, using Southeast (0.56%) and Red River Delta (1.81%) as development models [46]. The superior performance of Neural Networks (Table 5, Table S4, $R^2 = 0.993$) recommends applying machine learning for poverty prediction and resource allocation optimization, enhancing planning accuracy [47]. Uneven poverty reduction trends (Table S3) underscore the need for sustained support in lagging regions through sanitation and clean water infrastructure investments, ensuring sustainable progress toward SDG 1 and SDG 6 [48].

### 4.3 Comparison with Previous Studies

This study reinforces the relationship between infrastructure, economics, and multidimensional poverty but provides novelty through detailed analysis of Vietnam's six socio-economic regions, surpassing national or rural-urban comparative studies, highlighting the lag in Northern Midlands and Mountains and Central Highlands, consistent with findings on regional inequality in the U.S. and China [49], [50]. The application of Neural Networks (Table 5, Table S4, $R^2 = 0.993$) overcomes limitations of linear regression in prior studies, which struggled with nonlinear relationships, marking the first use of machine learning for regional poverty prediction in Vietnam, aligning with global trends in machine learning for poverty analysis [21], [26]. Sanitation access is quantified with a superior impact (correlation -0.84, PC1 loading 0.918), complementing studies on sanitation and community health, emphasizing a greater role than urban water supply, consistent with findings in Vietnam and Iran [23], [25]. Time-series analysis (Table S3) forecasts poverty and infrastructure trends, contributing novelty compared to studies focused on current conditions, supporting long-term policy planning, similar to approaches in Singapore and public-private partnership models [27], [28]. This study provides a more detailed basis for Vietnam, integrating regional inequality, machine learning, and long-term forecasting, guiding effective poverty reduction policies [54].

### 4.4 Limitations

This study, while providing significant insights, faces limitations affecting its accuracy and generalizability. The small sample size (N=42, 6 regions × 7 years) limits the robustness of models, particularly in time-series analysis (Table S3, $R^2$ ARIMA = 0.48), requiring larger datasets for improved reliability. Linear interpolation of missing data (subsection 2.1) may introduce slight bias, especially in regions with incomplete data, affecting regional analysis. The study focuses only on sanitation access, clean water, urban water supply, income, and expenditure, overlooking factors like education or health, critical to multidimensional poverty, narrowing the analysis scope. Neural Networks, despite superior performance (Table 5, $R^2$ = 0.993), exhibit a “black box” nature, hindering interpretability compared to linear regression, necessitating additional methods to clarify variable weights and interactions, limiting direct application to detailed policy planning [55].

### 4.5 Future Research

To address limitations and expand insights, future research directions are proposed to enhance accuracy and applicability. Collecting province- or district-level data will increase sample size, improving the robustness of time-series analysis (Table S3) and Neural Networks (Table 5), particularly in lagging regions. Integrating additional factors such as education, health, or gender equality will provide a comprehensive view of multidimensional poverty, overcoming current variable limitations. Applying advanced machine learning algorithms, such as Random Forests or Gradient Boosting, will further explore nonlinear interactions, enhancing prediction. Real-time data analysis with Neural Networks will support rapid policy decisions, especially in fast-changing contexts [56]. Finally, experimental studies evaluating the effectiveness of sanitation infrastructure investments in Northern Midlands and Mountains and Central Highlands will provide practical evidence, guiding sustainable poverty reduction policies [57].

## 5. Conclusion

This study analyzes multidimensional poverty across six socio-economic regions of Vietnam (Red River Delta, Northern Midlands and Mountains, North Central and Central Coast, Central Highlands, Southeast, Mekong River Delta) from 2016 to 2022, using panel data (N=42) and advanced methods such as principal component analysis (PCA, Table 3), linear regression (Table 4), and Neural Networks (Table 5). The results confirm significant regional disparities (Table 6), with Northern Midlands and Mountains (16.54%) and Central Highlands (13.39%) exhibiting high poverty rates and low sanitation access (81.56% and 80.59%), in contrast to Southeast (0.56%) and Red River Delta (1.81%).

The results validate three hypotheses: H1 is confirmed through the strong inverse relationship between infrastructure (sanitation access, clean water, urban water supply), economics (income, expenditure), and poverty (Table 2, Table 3, Table 4), emphasizing the need for infrastructure investment in lagging regions. H2 is supported by the superior performance of Neural Networks ($R^2$ = 0.993, Table 5) compared to linear regression, due to its ability to capture nonlinear relationships. H3 confirms sanitation access as a key factor (correlation -0.84, PC1 loading 0.918), surpassing urban water supply.

Policy recommendations include: prioritizing standard latrine construction in Northern Midlands and Mountains and Central Highlands; improving urban water supply in Central Highlands; allocating resources to lagging regions; and applying Neural Networks for forecasting and optimizing planning. While addressing many research gaps, limitations in sample size and variables necessitate expanding to province-level data and integrating education and health factors in future research, guiding sustainable poverty reduction strategies in Vietnam.

**References**

[1] "The Measurement of Multidimensional Poverty," 2009, pp. 139–150. doi: 10.1007/978-0-387-79253-8_6.

[2] P. Taylor, Ed., *Social Inequality in Vietnam and the Challenges to Reform*. ISEAS Publishing, 2004. doi: 10.1355/9789812305954.

[3] D. T. Nguyen, "Multidimensional poverty and human development of Vietnam in comparison with some Southeast Asian countries," *The Russian Journal of Vietnamese Studies*, vol. 6, no. 1, pp. 40–51, Jan. 2022, doi: 10.54631/VS.2022.61-105388.

[4] K. Z. Chen, R. Mao, and Y. Zhou, "Rurbanomics for common prosperity: new approach to integrated urban-rural development," *China Agricultural Economic Review*, vol. 15, no. 1, 2023, doi: 10.1108/CAER-12-2021-0256.

[5] C. Magazzino and M. Mele, "On the relationship between transportation infrastructure and economic development in China," *Research in Transportation Economics*, vol. 88, 2021, doi: 10.1016/j.retrec.2020.100947.

[6] Y. D. Wei, Y. Wu, W. Xiao, and X. Wu, "Preferences and Barriers of Vulnerable Urban Populations in Affordable Housing in Urban China," *J Urban Plan Dev*, vol. 149, no. 4, Dec. 2023, doi: 10.1061/JUPDDM.UPENG-4271.

[7] T. Van Tra, T. A. Nguyen, L. Van Linh, N. H. Bach, and D. H. Son, "The degree of integrated water resources management implementation in the Mekong River Delta in Viet Nam," *World Water Policy*, vol. 8, no. 1, 2022, doi: 10.1002/wwp2.12071.

[8] G. Galster and K. O. Lee, "Housing affordability: a framing, synthesis of research and policy, and future directions," *International Journal of Urban Sciences*, vol. 25, no. sup1, pp. 7–58, Jan. 2021, doi: 10.1080/12265934.2020.1713864.

[9] N. H. Dung and N. Van Cuong, "An assessment of multidimensional urban poverty in Vietnam central cities," *HCMCOUJS - ECONOMICS AND BUSINESS ADMINISTRATION*, vol. 5, no. 1, May 2020, doi: 10.46223/HCMCOUJS.econ.en.5.1.91.2015.

[10] N. Nofriani, "Machine Learning Application for Classification Prediction of Household's Welfare Status," *JITCE (Journal of Information Technology and Computer Engineering)*, vol. 4, no. 02, pp. 72–82, Sep. 2020, doi: 10.25077/jitce.4.02.72-82.2020.

[11] G. A. Makky and Al-Makky, "The regional distribution of Saudi Arabia's real estate development fund housing loans: Measuring inequality in housing distribution," *GeoJournal*, vol. 22, no. 1, pp. 49–57, Sep. 1990, doi: 10.1007/BF02428538.

[12] M. Yanto, Y. Wiyandra, and S. Defit, "Deep learning approach analysis model prediction and classification poverty status," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 1, p. 459, Mar. 2023, doi: 10.11591/ijai.v12.i1.pp459-468.

[13] A. G. Mekonnen, "Estimating Multidimensional Poverty: A New Methodological Approach," *J Poverty*, vol. 29, no. 2, pp. 110–128, Feb. 2025, doi: 10.1080/10875549.2023.2301620.

[14] "The Adoption of the Multidimensional Poverty Index in Developing Asia: Implications for Social Program Targeting and Inequality Reduction," *Jurnal Ekonomi Malaysia*, vol. 56, no. 3, Oct. 2022, doi: 10.17576/JEM-2022-5603-10.

[15] K. M. Alam, X. Li, S. Baig, O. Ghanem, and S. Hanif, "Causality between transportation infrastructure and economic development in Pakistan: An ARDL analysis," *Research in Transportation Economics*, vol. 88, 2021, doi: 10.1016/j.retrec.2020.100974.

[16] K. Shulla *et al.*, "Effects of COVID-19 on the Sustainable Development Goals (SDGs)," *Discover Sustainability*, vol. 2, no. 1, 2021, doi: 10.1007/s43621-021-00026-x.

[17] C. Zhang and F. Zhang, "Effects of Housing Prices on Income Inequality in Urban China," *Critical Housing Analysis*, vol. 2, no. 2, p. 1, 2015, doi: 10.13060/23362839.2015.3.2.237.

[18] S. Goli, N. K. Maurya, Moradhvaj, and P. Bhandari, "Regional Differentials in Multidimensional Poverty in Nepal: Rethinking Dimensions and Method of Computation," *Sage Open*, vol. 9, no. 1, Jan. 2019, doi: 10.1177/2158244019837458.

[19] J. Francis, R. Lee, I. S. Saimy, N. A. Mohamed Yusof, F. Ismail, and A. M. Zamri, "Comparative Study of Malaysian Affordable Housing Policy Initiatives," *Journal of Science, Technology and Innovation Policy*, vol. 9, no. 2, pp. 1–10, Jan. 2024, doi: 10.11113/jostip.v9n2.137.

[20] D. Van Le, T. Q. Tran, and T. Doan, "The private sector and multidimensional poverty reduction in Vietnam: A cross-province panel data analysis," *Int J Soc Welf*, vol. 31, no. 3, pp. 291–309, Jul. 2022, doi: 10.1111/ijsw.12524.

[21] T. Nguyen Phuong, A. Nguyen Ngoc, C. Nguyen Dieu, Y. Nguyen Thi Hoang, and H. Nguyen Van, "Xây dựng khung lý thuyết về năng lực nghề nghiệp giáo viên trong bối cảnh giáo dục phát triển bền vững tại Việt Nam," *Journal of Science Educational Science*, vol. 66, no. 3, 2021.

[22] J. J. Stanković, V. Janković-Milić, I. Marjanović, and J. Janjić, "An integrated approach of PCA and PROMETHEE in spatial assessment of circular economy indicators," *Waste Management*, vol. 128, 2021, doi: 10.1016/j.wasman.2021.04.057.

[23] H. T. T. Tran, H. T. T. Le, N. T. Nguyen, T. T. M. Pham, and H. T. Hoang, "The effect of financial inclusion on multidimensional poverty: the case of Vietnam," *Cogent Economics & Finance*, vol. 10, no. 1, Dec. 2022, doi: 10.1080/23322039.2022.2132643.

[24] A. Alsharkawi, M. Al-Fetyani, M. Dawas, H. Saadeh, and M. Alyaman, "Improved Poverty Tracking and Targeting in Jordan Using Feature Selection and Machine Learning," *IEEE Access*, vol. 10, pp. 86483–86497, 2022, doi: 10.1109/ACCESS.2022.3198951.

[25] J. C. Lopez, "Will Increasing Housing Supply Reduce Urban Inequality?," *Int Reg Sci Rev*, vol. 45, no. 4, pp. 383–416, Jul. 2022, doi: 10.1177/01600176211056232.

[26] A. Petrović, D. Manley, and M. van Ham, "Multiscale Contextual Poverty in the Netherlands: Within and Between-Municipality Inequality," *Appl Spat Anal Policy*, vol. 15, no. 1, pp. 95–116, Mar. 2022, doi: 10.1007/s12061-021-09394-3.

[27] G. Napoli, M. R. Trovato, and S. Giuffrida, "Housing Affordability and Income-threshold in Social Housing Policy," *Procedia Soc Behav Sci*, vol. 223, pp. 181–186, Jun. 2016, doi: 10.1016/j.sbspro.2016.05.345.

[28] S. Dhongde and R. Haveman, "Spatial and Temporal Trends in Multidimensional Poverty in the United States over the Last Decade," *Soc Indic Res*, vol. 163, no. 1, pp. 447–472, Aug. 2022, doi: 10.1007/s11205-022-02902-z.

[29] A. Dumont, "Changes in the U.S. Economy and Rural-Urban Employment Disparities," *FEDS Notes*, no. 2024-01-19–1, 2024, doi: 10.17016/2380-7172.3428.

[30] M. Marcos and G. Mera, "Migración, vivienda y desigualdades urbanas: condiciones socio-habitacionales de los migrantes regionales en Buenos Aires," *Revista INVI*, vol. 33, no. 92, pp. 53–86, May 2018, doi: 10.4067/S0718-83582018000100053.

[31] M. Bersisa and A. Heshmati, “A Distributional Analysis of Uni-and Multidimensional Poverty and Inequalities in Ethiopia,” *Soc Indic Res*, vol. 155, no. 3, pp. 805–835, Jun. 2021, doi: 10.1007/s11205-021-02606-w.

[32] Y. Zhang, G. Ma, Y. Tian, and Q. Dong, “Nonlinear Effect of Digital Economy on Urban–Rural Consumption Gap: Evidence from a Dynamic Panel Threshold Analysis,” *Sustainability (Switzerland)*, vol. 15, no. 8, 2023, doi: 10.3390/su15086880.

[33] Y. Dai and S. Zeng, “Effect of Digital Economy Development on Rural-Urban Income Disparity: Evidence from China,” *Proceedings of Business and Economic Studies*, vol. 5, no. 5, 2022, doi: 10.26689/pbes.v5i5.4415.

[34] N. Puttanapong, A. Martinez, J. A. N. Bulan, M. Addawe, R. L. Durante, and M. Martillan, “Predicting Poverty Using Geospatial Data in Thailand,” *ISPRS Int J Geoinf*, vol. 11, no. 5, p. 293, Apr. 2022, doi: 10.3390/ijgi11050293.

[35] A. Sharma, J. Rathod, R. Pol, and S. Gajbhiye, “Poverty Prediction Using Machine Learning,” *International Journal of Computer Sciences and Engineering*, vol. 7, no. 3, pp. 946–949, Mar. 2019, doi: 10.26438/ijcse/v7i3.946949.

[36] Q. Li, S. Yu, D. Échevin, and M. Fan, “Is poverty predictable with machine learning? A study of DHS data from Kyrgyzstan,” *Socioecon Plann Sci*, vol. 81, p. 101195, Jun. 2022, doi: 10.1016/j.seps.2021.101195.

[37] T. T.- Phuong, N. P.- Phuong, and L. N.- Son, “Why Foreign Direct Investment Has Not Promoted Social Housing Development in Vietnam,” *International Journal of Accounting and Economics Studies*, vol. 12, no. 4, pp. 483–490, Aug. 2025, doi: 10.14419/awvbza10.

[38] D. F. García Vélez and J. J. Núñez Velázquez, “Un enfoque alternativo para medir la pobreza multidimensional utilizando conjuntos difusos: análisis espacial para Ecuador,” *Investigaciones Regionales - Journal of Regional Research*, vol. 52, pp. 37–58, May 2022, doi: 10.38191/iirr-jorr.22.002.

[39] O. Bamiwuye, O. Akintunde, L. Jimoh, and K. Olanrewaju, “Perceived changes in food security, finances and revenue of rural and urban households during COVID-19 pandemic in Nigeria,” *Agrekon*, vol. 61, no. 3, 2022, doi: 10.1080/03031853.2022.2078847.

[40] T. Thai-Phuong, N. P.- Phuong, and L. Nguyen-Son, “Computational Efficiency of Latin Hypercube Sampling in Financial Risk Simulation: A Comparative Study,” *International Journal of Basic and Applied Sciences*, vol. 14, no. 4, pp. 412–424, Aug. 2025, doi: 10.14419/vq93sy72.

[41] P. P. Min, Y. W. Gan, S. N. B. Hamzah, T. S. Ong, and Md. S. Sayeed, “POVERTY PREDICTION USING MACHINE LEARNING APPROACH,” *Journal of Southwest Jiaotong University*, vol. 57, no. 1, pp. 136–146, Feb. 2022, doi: 10.35741/issn.0258-2724.57.1.12.

[42] L. Maruejols, H. Wang, Q. Zhao, Y. Bai, and L. Zhang, “Comparison of machine learning predictions of subjective poverty in rural China,” *China Agricultural Economic Review*, vol. 15, no. 2, pp. 379–399, May 2023, doi: 10.1108/CAER-03-2022-0051.

[43] N. V. Thanh and T. Van Dien, “Education as one of the fundamental factors of poverty reduction according to multi-dimensional poverty line in Vietnam,” *Perspectives of Science and Education*, vol. 64, no. 4, pp. 317–335, Sep. 2023, doi: 10.32744/pse.2023.4.19.

[44] S. D. Pratama, “The Role of Zakat in Alleviating Multidimensional Poverty,” *International Journal of Islamic Economics and Finance (IJIEF)*, vol. 6, no. 1, 2023, doi: 10.18196/ijief.v6i1.17006.

[45] K. Osmundsen and B. Bygstad, “Making sense of continuous development of digital infrastructures,” *Journal of Information Technology*, vol. 37, no. 2, 2022, doi: 10.1177/02683962211046621.

[46] M. Rozikin, A. B. Sulistyo, C. Saleh, Hermawan, and B. S. Riyadi, "The Collaborative Governance in Digital Infrastructure Development in Indonesia: A Public Policy Perspective," *International Journal of Membrane Science and Technology*, vol. 10, no. 3, 2023, doi: 10.15379/ijmst.v10i3.1553.

[47] P. Prus and M. Sikora, "The impact of transport infrastructure on the sustainable development of the region—case study," *Agriculture (Switzerland)*, vol. 11, no. 4, 2021, doi: 10.3390/agriculture11040279.

[48] B. D. Dhungel, "Infrastructure Development and Economic Growth in Nepal," *Management Dynamics*, vol. 23, no. 2, 2020, doi: 10.3126/md.v23i2.35817.

[49] H. Dong, "The impact of income inequality on rental affordability: An empirical study in large American metropolitan areas," *Urban Studies*, vol. 55, no. 10, pp. 2106–2122, Aug. 2018, doi: 10.1177/0042098017710380.

[50] C. Zhang, S. Jia, and R. Yang, "Housing affordability and housing vacancy in China: The role of income inequality," *J Hous Econ*, vol. 33, pp. 4–14, Sep. 2016, doi: 10.1016/j.jhe.2016.05.005.

[51] A. Hailemariam, S. Awaworyi Churchill, R. Smyth, and K. T. Baako, "Income inequality and housing prices in the very long-run," *South Econ J*, vol. 88, no. 1, pp. 295–321, Jul. 2021, doi: 10.1002/soej.12520.

[52] S. J. Samsam Shariat, A. Zarrabi, and M. Taghvaei, "Analysis of the Low-Income Housing in Isfahan Metropolis," *Mod Appl Sci*, vol. 11, no. 3, p. 120, Jan. 2017, doi: 10.5539/mas.v11n3p120.

[53] A. Alwehab and M. Q. A. G. Al Ani, "An inductive perspective of Singapore Housing Policy: a Comparative Study," *Acta Scientiarum Polonorum Administratio Locorum*, vol. 21, no. 4, pp. 479–488, Dec. 2022, doi: 10.31648/aspal.7516.

[54] D. Ben-Shahar and J. Warszawski, "Inequality in housing affordability: Measurement and estimation," *Urban Studies*, vol. 53, no. 6, pp. 1178–1202, May 2016, doi: 10.1177/0042098015572529.

[55] A. Can, "Housing and urbanization policies of Istanbul, Turkey from central to the local," *Urban Res Pract*, vol. 15, no. 3, pp. 454–463, May 2022, doi: 10.1080/17535069.2022.2085376.

[56] N. P. Aryani and I. K. M. Wijaya, "Comparison of Residential Patterns and Influence Analysis of Cultural, Economic and Social Aspects on the Dualism of Residential Patterns in Pengotan Traditional Village, Bangli, Bali," *Civil Engineering and Architecture*, vol. 13, no. 1, pp. 21–40, Jan. 2025, doi: 10.13189/cea.2025.130102.

[57] I. Adedeji, "Nigerian Urbanization and the Significance of Affordable Housing," *Journal of Service Science and Management*, vol. 16, no. 03, pp. 351–368, 2023, doi: 10.4236/jssm.2023.163020.

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**Appendix**

**Table S1.** Descriptive Statistics by Year

| Year | Variable | Mean | Std Dev | Min | Max | Median | IQR |
|---|---|---|---|---|---|---|---|
| 2016 | Poverty Rate (%) | 10.96 | 8.62 | 0.99 | 23.04 | 10.07 | 17.12 |
| 2016 | Clean Water Access (%) | 92.35 | 6.77 | 81.00 | 99.50 | 92.25 | 11.30 |
| 2016 | Urban Water Supply (%) | 79.42 | 9.97 | 62.30 | 91.90 | 80.20 | 13.18 |
| 2016 | Sanitation Access (%) | 83.20 | 12.33 | 70.90 | 99.40 | 80.65 | 24.98 |
| 2016 | Income Per Capita (USD) | 135.45 | 47.24 | 88.59 | 210.38 | 116.07 | 82.03 |
| 2016 | Expenditure Per Capita (USD) | 95.13 | 24.48 | 74.69 | 136.19 | 83.06 | 41.15 |
| 2017 | Poverty Rate (%) | 9.86 | 7.94 | 0.86 | 20.97 | 8.80 | 15.89 |
| 2017 | Clean Water Access (%) | 93.32 | 6.14 | 82.85 | 99.60 | 93.38 | 10.11 |
| 2017 | Urban Water Supply (%) | 80.23 | 10.53 | 62.40 | 90.00 | 81.50 | 17.40 |
| 2017 | Sanitation Access (%) | 85.21 | 11.14 | 74.10 | 99.50 | 82.83 | 22.56 |
| 2017 | Income Per Capita (USD) | 146.17 | 52.00 | 95.40 | 230.96 | 127.24 | 88.04 |
| 2017 | Expenditure Per Capita (USD) | 97.77 | 26.59 | 74.69 | 141.35 | 84.96 | 45.59 |
| 2018 | Poverty Rate (%) | 8.21 | 6.90 | 0.64 | 18.35 | 7.24 | 13.42 |
| 2018 | Clean Water Access (%) | 94.27 | 5.52 | 84.70 | 99.70 | 94.45 | 8.92 |
| 2018 | Urban Water Supply (%) | 84.57 | 10.78 | 64.10 | 93.00 | 87.40 | 14.20 |
| 2018 | Sanitation Access (%) | 87.20 | 9.98 | 77.20 | 99.60 | 85.00 | 20.15 |
| 2018 | Income Per Capita (USD) | 165.91 | 55.93 | 108.62 | 252.61 | 146.08 | 100.36 |
| 2018 | Expenditure Per Capita (USD) | 110.38 | 23.66 | 88.49 | 148.22 | 98.91 | 40.95 |
| 2019 | Poverty Rate (%) | 7.18 | 6.23 | 0.49 | 16.43 | 6.11 | 12.09 |
| 2019 | Clean Water Access (%) | 94.30 | 6.06 | 83.70 | 99.90 | 95.25 | 10.15 |
| 2019 | Urban Water Supply (%) | 87.30 | 10.65 | 66.60 | 94.90 | 90.65 | 13.52 |
| 2019 | Sanitation Access (%) | 88.83 | 9.68 | 77.50 | 99.90 | 87.75 | 19.42 |
| 2019 | Income Per Capita (USD) | 175.27 | 60.03 | 113.67 | 270.45 | 155.39 | 106.88 |
| 2019 | Expenditure Per Capita (USD) | 112.06 | 25.93 | 88.41 | 152.39 | 100.21 | 47.22 |
| 2020 | Poverty Rate (%) | 6.29 | 5.52 | 0.32 | 14.38 | 5.35 | 10.75 |
| 2020 | Clean Water Access (%) | 96.05 | 4.99 | 86.40 | 99.90 | 97.10 | 6.22 |
| 2020 | Urban Water Supply (%) | 89.27 | 9.77 | 69.70 | 96.40 | 92.25 | 8.80 |
| 2020 | Sanitation Access (%) | 91.53 | 7.01 | 84.70 | 99.90 | 89.85 | 14.80 |
| 2020 | Income Per Capita (USD) | 171.99 | 56.63 | 118.29 | 259.63 | 156.78 | 108.77 |
| 2020 | Expenditure Per Capita (USD) | 118.95 | 30.73 | 90.82 | 169.35 | 109.02 | 56.10 |
| 2021 | Poverty Rate (%) | 5.74 | 5.15 | 0.25 | 13.43 | 4.75 | 9.93 |

| Year | Variable | Mean | Std Dev | Min | Max | Median | IQR |
|---|---|---|---|---|---|---|---|
| 2021 | Clean Water Access (%) | 97.07 | 4.09 | 89.00 | 99.90 | 98.10 | 4.60 |
| 2021 | Urban Water Supply (%) | 97.07 | 4.09 | 89.00 | 99.90 | 98.10 | 4.60 |
| 2021 | Sanitation Access (%) | 93.55 | 5.56 | 87.20 | 99.70 | 93.15 | 11.50 |
| 2021 | Income Per Capita (USD) | 172.22 | 52.41 | 123.65 | 252.53 | 157.04 | 103.71 |
| 2021 | Expenditure Per Capita (USD) | 117.91 | 29.87 | 88.85 | 163.66 | 107.07 | 56.22 |
| 2022 | Poverty Rate (%) | 5.67 | 5.12 | 0.37 | 12.82 | 4.57 | 10.51 |
| 2022 | Clean Water Access (%) | 97.65 | 2.86 | 92.10 | 99.80 | 98.20 | 3.70 |
| 2022 | Urban Water Supply (%) | 97.65 | 2.86 | 92.10 | 99.80 | 98.20 | 3.70 |
| 2022 | Sanitation Access (%) | 95.00 | 4.14 | 91.10 | 99.80 | 94.15 | 8.45 |
| 2022 | Income Per Capita (USD) | 186.55 | 54.27 | 134.32 | 268.39 | 170.42 | 106.73 |
| 2022 | Expenditure Per Capita (USD) | 112.70 | 28.35 | 83.47 | 151.69 | 101.80 | 54.71 |

**Table S2.** Variance Inflation Factors for Standardized Variables

| Variable | VIF |
|---|---|
| Clean Water Access Std | 3.198 |
| Urban Water Supply Std | 2.360 |
| Sanitation Access Std | 5.097 |
| Income Per Capita USD Std | 20.484 |
| Expenditure Per Capita USD Std | 18.966 |

**Table S3.** National Time Series Analysis Results (2016–2022, Forecasts 2023–2025)

| Variable | Model | AR1 | Level | Trend | $R^2$ | RMSE | Forecast 2023 | Forecast 2024 | Forecast 2025 |
|---|---|---|---|---|---|---|---|---|---|
| Poverty Rate (%) | ARIMA(1,0,0) | 0.91 | - | - | 0.48 | 1.18 | 5.50 | 5.30 | 5.10 |
| Clean Water Access (%) | Double Exponential Smoothing | - | 97.50 | 0.30 | 0.95 | 0.30 | 98.00 | 98.30 | 98.60 |
| Income Per Capita (USD) | Double Exponential Smoothing | - | 180.00 | 2.50 | 0.90 | 5.00 | 190.00 | 192.50 | 195.00 |

**Table S4.** Cross-Validation Results for Neural Networks (Case 5)

| Fold | $R^2$ (Training) | $R^2$ (Validation) | RMSE (Training) | RMSE (Validation) | Mean Abs Dev (Training) | Mean Abs Dev (Validation) |
|---|---|---|---|---|---|---|
| Fold 1 | 0.993 | 0.986 | 0.082 | 0.105 | 0.060 | 0.083 |
| Fold 2 | 0.994 | 0.989 | 0.080 | 0.102 | 0.059 | 0.081 |
| Fold 3 | 0.993 | 0.987 | 0.081 | 0.104 | 0.059 | 0.083 |
| Fold 4 | 0.992 | 0.988 | 0.083 | 0.103 | 0.061 | 0.082 |
| Fold 5 | 0.994 | 0.989 | 0.081 | 0.103 | 0.059 | 0.082 |
| Average | 0.993 | 0.988 | 0.082 | 0.103 | 0.060 | 0.082 |

**Table S5.** Regional Comparison of Urban Water Supply (2016–2022)

| Region | Mean (%) | Std Dev (%) | N | Min (%) | Max (%) |
|---|---|---|---|---|---|
| Central Highlands | 74.34 | 16.13 | 7 | 62.30 | 97.90 |
| Mekong River Delta | 91.43 | 5.60 | 7 | 84.80 | 98.50 |
| North Central and Central Coast | 86.97 | 8.96 | 7 | 76.00 | 97.80 |
| Northern Midlands and Mountains | 86.31 | 6.28 | 7 | 77.70 | 92.50 |
| Red River Delta | 93.73 | 6.07 | 7 | 82.70 | 99.90 |
| Southeast | 94.79 | 3.79 | 7 | 90.00 | 99.90 |

**Table S6.** Tukey HSD and Student's t Pairwise Comparisons for Urban Water Supply by Region

| Pairwise Comparison (Region - Region) | Difference | Std Error | t Ratio | Prob > \|t\| (Tukey HSD) | Lower 95% (Tukey HSD) | Upper 95% (Tukey HSD) | Prob > \|t\| (Student's t) | Lower 95% (Student's t) | Upper 95% (Student's t) |
|---|---|---|---|---|---|---|---|---|---|
| Central Highlands - Mekong River Delta | -17.0857 | 4.6920 | -3.6400 | 0.0101 | -31.2021 | -2.9693 | 0.0008 | -26.6016 | -7.5698 |
| Central Highlands - North Central and Central Coast | -12.6286 | 4.6920 | -2.6900 | 0.1019 | -26.7449 | 1.4878 | 0.0107 | -22.1445 | -3.1127 |
| Central Highlands - Northern Midlands and Mountains | -11.9714 | 4.6920 | -2.5500 | 0.1363 | -26.0878 | 2.1449 | 0.0151 | -21.4873 | -2.4555 |
| Central Highlands - Red River Delta | -19.3857 | 4.6920 | -4.1300 | 0.0026 | -33.5021 | -5.2693 | 0.0002 | -28.9016 | -9.8698 |
| Central Highlands - Southeast | -20.4429 | 4.6920 | -4.3600 | 0.0014 | -34.5592 | -6.3265 | 0.0001 | -29.9588 | -10.9270 |
| Mekong River Delta - North Central and Central Coast | 4.4571 | 4.6920 | 0.9500 | 0.9304 | -9.6592 | 18.5735 | 0.3485 | -5.0588 | 13.9730 |
| Mekong River Delta - Northern Midlands and Mountains | 5.1143 | 4.6920 | 1.0900 | 0.8822 | -9.0021 | 19.2307 | 0.2830 | -4.4016 | 14.6302 |
| Mekong River Delta - Red River Delta | -2.3000 | 4.6920 | -0.4900 | 0.9962 | -16.4164 | 11.8164 | 0.6270 | -11.8159 | 7.2159 |
| Mekong River Delta - Southeast | -3.3571 | 4.6920 | -0.7200 | 0.9788 | -17.4735 | 10.7592 | 0.4789 | -12.8730 | 6.1588 |
| North Central and Central Coast - Northern Midlands and Mountains | 0.6571 | 4.6920 | 0.1400 | 1.0000 | -13.4592 | 14.7735 | 0.8894 | -8.8588 | 10.1730 |
| North Central and Central Coast - Red River Delta | -6.7571 | 4.6920 | -1.4400 | 0.7029 | -20.8735 | 7.3592 | 0.1585 | -16.2730 | 2.7588 |
| North Central and Central Coast - Southeast | -7.8143 | 4.6920 | -1.6700 | 0.5625 | -21.9307 | 6.3021 | 0.1045 | -17.3302 | 1.7016 |
| Northern Midlands and Mountains - Red River Delta | -7.4143 | 4.6920 | -1.5800 | 0.6164 | -21.5307 | 6.7021 | 0.1228 | -16.9302 | 2.1016 |
| Northern Midlands and Mountains - Southeast | -8.4714 | 4.6920 | -1.8100 | 0.4751 | -22.5878 | 5.6449 | 0.0794 | -17.9873 | 1.0445 |
| Red River Delta - Southeast | -1.0571 | 4.6920 | -0.2300 | 0.9999 | -15.1735 | 13.0592 | 0.8230 | -10.5730 | 8.4588 |