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Mapping Regional Inequality and Household Economic Stratification in East Nusa Tenggara Based on a Wealth Index

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Abstract

Conventional monetary-based economic measurement is often biased, particularly in regions with a dominant informal sector and seasonal income fluctuations. This research aims to construct a Wealth Index in East Nusa Tenggara (NTT) Province as a more stable proxy for long-term welfare. Using microdata from the 2025 National Socio-Economic Survey (*SUSENAS*), the weighted *principal component analysis* (PCA) method was applied to 18 binary-transformed household asset variables. The analysis utilized R statistical software to ensure accurate population stratification into five welfare quintiles. Statistical validation results showed a Kaiser–Meyer–Olkin (KMO) value of 0.84 and a highly significant Bartlett's test ($p < 0.001$), indicating excellent data suitability. The first principal component (PC1) was selected as the single index capable of explaining 20.84% of the total data variance. Loading factor analysis revealed that tertiary asset ownership, such as computers, air conditioners, and cars, possessed the highest discriminatory power, concentrated in Quintile 5 (richest), while households in Quintile 1 (poorest) were characterized by *deprivational* basic housing conditions. Spatially, an extreme center–periphery divide was identified, with welfare concentrated in urban areas such as Kupang City, while outer archipelagic regions remain underdeveloped. This study recommends asymmetric, place-based policy interventions, prioritizing basic infrastructure development in identified poverty pockets. Furthermore, the generated index is recommended as a robust proxy for modeling ability to pay in actuarial pricing and microinsurance schemes for the informal sector.

Keywords:
Wealth Index; Principal Component Analysis (PCA); East Nusa Tenggara; Socio-Economic Status; SUSENAS 2025

INTRODUCTION

Socioeconomic status is a key determinant in public policy analysis, development economics, and epidemiology (Chaquila & Pereyra-Elías, 2026; Cunha, Cruz, Martins-Pfeifer, Costa, & Abreu, 2026). Accurately mapping economic status is crucial for identifying vulnerable groups and evaluating inequality in access to basic services such as health and education (Hossain et al., 2025; Kim, Kang, & Hwang, 2025; Li et al., 2025). Conventionally, economic status is often measured using direct monetary indicators, specifically household income or expenditure. However, in developing countries and regions with a large informal sector, monetary data are often inaccurate due to high reporting bias and seasonal income fluctuations (Hounkpatin et al. 2019).

The main issues with monetary data are the high risk of reporting bias, short-term income volatility due to seasonal factors, and respondents' reluctance to disclose their true financial conditions (Afzal, 2025; Chowdhury, Mahdzan, & Rahman, 2024; Wankhade, 2025). Recent systematic studies show that measurement errors in income data can distort inequality analysis, leading to policy recommendations that are not well targeted (Poirier et al. 2020). In response to these limitations, the paradigm of measuring welfare has shifted toward an asset-based approach. This approach views the ownership of physical assets—such as housing conditions, vehicles, and electronics—as a representation of long-term wealth accumulation. These assets are more stable and less vulnerable to temporary economic fluctuations (Chakraborty et al. 2016). This is supported by Onemolease and Akioya (2020), who state that using an asset index can minimize criticism of monetary measures, which often fail to capture the reality of welfare in rural areas.

The main methodological challenge in the asset approach is how to aggregate various types of categorical ownership variables into a single standardized index. The most robust and widely accepted statistical method to address this is Principal Component Analysis (PCA). PCA works by reducing the dimensions of complex data into one principal component capable of explaining the largest variance in household economic status (Da Vieira et al. 2022). Specifically, this procedure requires transforming raw data into binary variables (values of 0 and 1), after which PCA assigns an objective weight to each asset. Assets that are more rarely owned by the population receive a larger positive weight, which indicates a higher economic status (Moez et al. 2022).

The application of PCA produces a continuous wealth score that allows for ranking households from the poorest to the richest. For comparative analysis and policy targeting, this continuous score is classified into operational strata. The current standard is to stratify the score into five equal percentile groups, or quintiles, ranging from Quintile 1 to Quintile 5 (Razavi et al. 2025a). This grouping effectively distinguishes sociodemographic characteristics between strata with sharp discrimination (Venugopal et al. 2021), enabling more meaningful policy inferences compared with simple income quintiles.

Several studies have examined the construction of wealth indices using asset-based approaches and PCA methodology across various contexts. Filmer and Pritchett (2001) established the methodological foundation for using asset indices as proxies for long-term economic status in developing countries. Chakraborty et al. (2016) confirmed that reduced asset sets could maintain adequate reliability for health equity analysis across 16 countries, while Vyas and Kumaranayake (2006) provided comprehensive guidance on PCA methodology, emphasizing KMO and Bartlett's test validation. In Africa, Onemolease and Akioya (2020) demonstrated that asset indices minimize monetary-measure limitations in rural contexts, and Mwansa (2023) validated that PC1 typically explains 20–30% of variance in large-scale socioeconomic data. More recently, Razavi et al. (2025a, 2025b) established standard protocols for weighted quintile stratification, Tareq et al. (2021) confirmed that incorporating sampling weights produces more accurate population estimates, while La and Vu (2025) and Xie et al. (2023) demonstrated the utility of asset-based approaches in Southeast Asian and African contexts, respectively.

Despite this extensive literature, significant research gaps remain. Most previous studies have focused on national-level or cross-country analyses, with limited attention to provincial-level contexts with unique geographic characteristics such as archipelagic regions. Research specifically constructing wealth indices for East Nusa Tenggara (NTT) Province—which has a distinct archipelagic geography, dynamic poverty rates, and a large informal sector—is still scarce. The novelty of this research lies in applying PCA to construct a wealth index for NTT using the most recent 2025 SUSENAS microdata, incorporating survey weights into both PCA calculation and quintile stratification to accurately represent population structure, combining statistical analysis with spatial visualization to map welfare distribution across all districts and cities, revealing the center–periphery divide, and providing a robust proxy for modeling ability to pay in microinsurance schemes where verified income data are often unavailable.

The urgency of this method is evident in the development context of Indonesia, particularly in East Nusa Tenggara (NTT) Province. As an archipelago with unique geographic challenges and dynamic poverty rates, a monetary approach alone is insufficient to capture the full picture of local welfare (La and Vu 2025). Therefore, using large-scale household survey data that include asset details in NTT is crucial for obtaining a more stable welfare proxy. This study aims to construct a population wealth index by applying the PCA method to binarized asset variables using a population dataset in NTT Province. Specifically, this research classifies the population into five welfare quintiles to provide valid economic stratification. The stratification results are expected to serve as a reliable instrument for mapping inequality and supporting precise development intervention targeting in the NTT region.

RESEARCH METHOD

This study applied a quantitative descriptive approach to construct a population wealth index in East Nusa Tenggara (NTT) Province. The primary data used is secondary microdata from the 2025 National Socio-Economic Survey (SUSENAS). The year 2025 was selected to capture the most recent socio-economic conditions following various global and national economic dynamics. The unit of analysis in this study is households domiciled in the NTT region, selected due to its archipelagic geographic characteristics and specific development equity challenges.

Table 1. Survey question variables for Wealth-Indexing

Variable	Question
R1606	What is the main construction material of the widest roof?
R1607	What is the main construction material of the widest walls?
R1608	What is the main construction material of the widest floor?
R1609B	What type of toilet facility is used?
R1609C	Where is the final disposal site for human waste?
R1610A	What is the main source of drinking water?
R1616	What is the main source of lighting?
R1616B1	What is the installed power capacity at meter 1?
R1616B2	What is the installed power capacity at meter 2?
R1616B3	What is the installed power capacity at meter 3?

R1801A	Does the household own a 5.5 kg gas cylinder or larger?
R1801B	Does the household own a refrigerator?
R1801C	Does the household own an air conditioner (AC)?
R1801F	Does the household own a computer/laptop?
R1801G	Does the household own gold/jewelry (minimum 10 grams)?
R1801H	Does the household own a motorcycle?
R1801K	Does the household own a car?
R1801M	Does the household own land?

Source: SUSENAS 2025, processed by the researcher

The variables collected in this study focus on the dimensions of asset ownership and housing feasibility as proxies for long-term welfare. These variables include physical building characteristics (such as roof, wall, and floor types), housing facilities (main lighting source, drinking water source, and sanitation availability), and ownership of durable goods (such as refrigerators, televisions, mobile phones, and motor vehicles). Since the statistical analysis requires numerical input, all categorical variables from the SUSENAS questionnaire were transformed through a dichotomization process into binary variables (dummy variables). In this process, each asset category is given a value of 1 if the household owns the asset or has decent housing conditions, and a value of 0 if they do not. This approach is the current standard to ensure that every variable has a proportional weight in forming the composite index (Xie et al. 2023).

The data analysis technique used is Principal Component Analysis (PCA) to reduce the dimensions of the binary asset variable set into a single composite indicator. The analysis procedure begins with a data feasibility test using the Kaiser-Meyer-Olkin (KMO) parameter and Bartlett's Test of Sphericity to ensure that the intercorrelation between variables is adequate (Rembulan et al. 2020). Once the assumptions are met, this study uses a Weighted PCA approach, where household sampling weights from SUSENAS are included in the calculation. This is done to guarantee that the formed variance represents the actual population structure of NTT (Tareq et al. 2021). The First Principal Component (PC1) is then extracted as the wealth index because of its ability to explain the largest proportion of variance in the entire dataset (Takwin et al. 2025). The weights or factor scores generated from this component are then used to calculate the specific wealth score for each household additively based on its asset ownership. Mathematically, the wealth score for the i-th household (Y_i) is calculated using the following linear equation (Filmer and Pritchett 2001):

$$Y_i = \sum_{k=1}^{n} w_k \left(\frac{f_{ik} - \overline{f_k}}{s_k} \right) \quad (1)$$

Where w_k is the loading factor for the k-th asset, f_{ik} is the asset value (0 or 1) for household i, while $\overline{f_k}$ and s_k are the mean and standard deviation of that asset.

The final stage of this analysis is to perform socio-economic stratification based on the continuous wealth scores obtained. The household population is grouped into five weighted quantiles. This stratification explicitly incorporates survey sampling weights to ensure that each quintile represents exactly 20% of the real population of NTT, rather than merely 20% of the sample observations (Razavi et al. 2025b). The strata range from Quintile 1, representing the poorest 20% of the population, to Quintile 5, representing the richest 20%. The entire process of data management, variable transformation, PCA weight calculation, and weighted stratification was carried out using R statistical software to ensure analysis accuracy and reproducibility.

RESULTS AND DISCUSSION

Data Processing

Before proceeding to the dimension reduction stage to construct the wealth index, the fundamental step was to verify the data suitability. The first test was conducted using Bartlett's Test of Sphericity to detect the presence of inter-variable correlations. The null hypothesis (H_0) in this test states that the population correlation matrix is an identity matrix, meaning each asset variable is independent and unrelated. The statistical calculation resulted in a very large Chi-Square (χ^2) value of $33{,}814.59$, with degrees of freedom (df) corresponding to the number of asset variable interactions tested. The obtained probability significance value (p-value) was 0.000 ($p < 0{,}001$). Since the p-value is far below the significance level ($\alpha = 0.05$), there is strong statistical evidence to reject the null hypothesis. This confirms that using a data reduction method like PCA is appropriate and valid.

Table 2. MSA values for each survey question variable

Asset Variable	MSA Value
R1606	0,74
R1607	0,86
R1608	0,87
R1609B	0,68
R1609C	0,71
R1610A	0,84
R1616	0,84
R1616B1	0,91
R1616B2	0,69
R1616B3	0,53
R1801A	0,85
R1801B	0,87
R1801C	0,86
R1801F	0,90
R1801G	0,89
R1801H	0,89
R1801K	0,90
R1801M	0,41

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

Furthermore, to measure how appropriate the samples and variables used were, the Kaiser-Meyer-Olkin (KMO) value was calculated. Unlike Bartlett's test which looks at relationship significance, KMO measures the proportion of variance caused by underlying factors. The analysis results showed an Overall KMO value of 0.84. Referring to the standard classification established by Kaiser (1974), this value falls into the "Meritorious" category (Excellent), as it is well above the minimum threshold of 0.50 and exceeds the adequacy limit of 0.80. Interpretatively, a KMO of 0.84 indicates that the set of asset variables used in this study is highly coherent. This aligns with methodological guidelines from Vyas and Kumaranayake (2006), stating that a high KMO value guarantees that the generated principal component will be stable and optimal. Additionally, the examination of the Measure of Sampling Adequacy (MSA) at the individual variable level showed consistency, where the majority of asset variables had MSA values above 0.50 (see Table 2).

PCA and Wealth-Indexing Results

Principal Component Analysis was performed on the 18 transformed asset variables. The determination of which component to use as the wealth index representation was based on the proportion of variance explained by each component.

Table 3. Descriptive statistics of PCA components

	Standard Deviation	Proportion of Variance	Cumulative Variance
PC1	1,9366	0,2084	0,2084
PC2	1,29051	0,09252	0,30089
PC3	1,07909	0,06469	0,36558
PC4	1,03755	0,05981	0,42539
PC5	1,00637	0,05627	0,48165
PC6	0,99709	0,05523	0,53689
PC7	0,9749	0,0528	0,5897
PC8	0,91917	0,04694	0,63662
PC9	0,9161	0,04662	0,68324
PC10	0,8879	0,0438	0,727
PC11	0,8611	0,0412	0,7682
PC12	0,8496	0,0401	0,8083
PC13	0,82288	0,03762	0,84596
PC14	0,80894	0,03635	0,88232
PC15	0,79065	0,03473	0,91704
PC16	0,76065	0,03214	0,94919
PC17	0,69006	0,02645	0,97564
PC18	0,66213	0,02436	1

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

Based on the analysis results, the First Principal Component (PC1) was selected as the single proxy to measure the socio-economic status of the population. The extraction results show that PC1 has a standard deviation of 1.9366 and is capable of explaining 20.84% of the total data variance. Although this number may not seem large statistically, such a proportion is very reasonable for large-scale socio-economic data. Recent studies by Razavi et al. (2025b) and Mwansa (2023) also show that in constructing wealth indices using census or national survey data, the first principal component generally explains a range of 20% to 30% of the total variance. Mwansa (2023) specifically explains that PC1 captures the systematic "long-term wealth" dimension, while the second component and onwards (PC2, PC3, etc.) tend to capture residual variations or region-specific characteristics that are irrelevant for a national welfare index.

The analysis continued by examining the internal structure of the component through factor loadings, as shown in Table 4. These values represent the correlation between each asset variable and the formed wealth index.

Table 4. Asset statistics and Loading Factors

Variable	Asset Description	Ownership Proportion (Mean)	Loading Factor
R1801B	Refrigerator	0,208	0,371
R1608	Floor material (Main)	0,18	0,349
R1801F	Computer/Laptop	0,093	0,319
R1616B1	Electricity Meter 1 (Power)	0,122	0,299
R1801K	Car	0,049	0,287
R1801C	Air Conditioner (AC)	0,01	0,27
R1607	Wall Material (Main)	0,551	0,253
R1801G	Gold/Jewellery (>10g)	0,026	0,249
R1801A	Gas Cylinder (5,5 kg+)	0,013	0,238
R1801H	Motorcycle	0,519	0,234
R1609C	Waste Disposal Site	0,602	0,225
R1609B	Toilet Type	0,777	0,213
R1616	Main Lighting Source	0,833	0,201
R1610A	Drinking Water Source	0,264	0,11
R1616B2	Electricity Meter 2 (Power)	0,003	0,086
R1606	Roof Material (Main)	0,01	0,029
R1616B3	Electricity Meter 3 (Power)	0	0,027
R1801M	Land Ownership	0,89	0,005

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

Based on Table 4, a sharp and logical polarization is visible between modern asset ownership and traditional housing conditions. The variables with the highest loading factors are dominated by the ownership of tertiary durable goods, such as cars, ACs, and computers/laptops. The high value of these loadings indicates that the ownership of these assets has very strong discriminatory power. This means that households owning cars, ACs, and laptops are almost certainly in the top wealth quintile in East Nusa Tenggara. Conversely, the smallest positive values are found in land ownership and roof materials. The consistency of positive signs for high-economic-value assets shows that the PCA model constructed has good internal coherence.

Wealth Score Calculation and Stratification

Once the loading factors for each asset variable were obtained, the next step was to calculate the individual wealth score for every household in the sample. This process involved summing the asset ownership values multiplied by their respective weights. Through this calculation, every resident in NTT Province received a single standardized continuous score. A positive score indicates ownership of high-weighted.

Table 5. Percentage of asset ownership for each variable across quintiles

Variable	Percentage (%)				
	Q1	Q2	Q3	Q4	Q5
R1606	16,45	11,48	4,25	32,22	35,6
R1607	5,2	10,25	23,53	28,75	32,27
R1608	0,29	1,37	1,29	26,9	70,15
R1609B	7,83	19,09	23,9	24,57	24,61
R1609C	4,82	15,77	23,73	26,86	28,82
R1610A	6,21	14,6	23,39	18,8	37
R1616	12,64	18,54	22,29	23,06	23,48
R1616B1	0	0,53	3,7	24,14	71,63
R1616B2	0	0	0	3,05	96,95
R1616B3	0	0	0	0	100
R1801A	0	0	0	0	100
R1801B	0	1,91	1,41	22,39	74,29
R1801C	0	0	0	0	100
R1801F	0	0,98	1,71	9,51	87,81
R1801G	0	0	3,98	2,97	93,04
R1801H	6,58	12,1	18,98	29,01	33,33
R1801K	0	0,79	0	6,43	92,78
R1801M	21,32	18,14	19,86	20,74	19,94

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

assets and decent housing conditions, classifying the household as having a higher socio-economic status. Conversely, a negative score indicates the absence of these assets or housing conditions below the provincial average.

To make the analysis more operational for policy purposes, these raw scores were not used directly but were stratified into five equal ordinal groups or quintiles (Q1–Q5). As previously mentioned, this division explicitly used survey weights to ensure that each quintile represented 20% of the total population. Quintile 1 represents the poorest 20% of the population, while Quintile 5 represents the richest 20%. This classification serves as the basis for dissecting the asset ownership profile shown in Table 5.

Profile of Welfare Quintiles

In the Quintile 1 group (the poorest 20%), the population characteristics are dominated by basic asset deprivation. It is evident that the ownership of high-value assets such as cars and air conditioners is non-existent (0%). Meanwhile, housing quality indicators show concerning conditions, where the percentage of residents with dirt floors and non-permanent walls is quite significant. This indicates that this group is not only poor in terms of financial assets but also vulnerable regarding basic infrastructure feasibility.

In contrast, a drastic surge in asset ownership occurs in Quintile 5 (the richest 20%). Almost all tertiary asset ownership, such as cars, computers, and AC facilities, is concentrated in this group. For example, car ownership reaches 92.78% in the top quintile, which is inversely proportional to the bottom quintile. The sharp disparity between Q1 and Q5 in Table 5 serves as empirical evidence that the constructed Wealth Index has successfully separated the NTT population into accurate and robust economic strata.

This finding is consistent with the socio-economic structure in East Nusa Tenggara, where this wealth index provides a more stable picture of long-term welfare compared to expenditure data, which is often fluctuating. This aligns with the argument by Onemolease and Akioya (2020), stating that fusing an asset index can minimize reporting bias. Additionally, the low contribution of land ownership (R1801M) in the PCA model is confirmed here; land ownership is spread relatively evenly across all quintiles (around 18-21%). This shows that in the agrarian context of NTT, owning land does not necessarily reflect high economic welfare.

Spatial Analysis of Welfare

The transition from statistical quintile analysis to regional mapping is crucial for identifying spatial inequalities in East Nusa Tenggara Province. Given NTT's geographic characteristic as an archipelago, the individual wealth scores (PC1) were aggregated to the district/city level using a population-weighted mean technique to produce a more accurate regional welfare profile. As emphasized by Mwansa (2023) and Chakraborty et al. (2016), spatial visualization is necessary to identify "poverty pockets" that are often invisible in macro-level provincial analyses.

The distribution of wealth index scores is visualized in Fig. 1 through five separate maps corresponding to each quintile. In these maps, darker colors indicate a higher concentration of the population in that specific quintile, while lighter colors represent a lower distribution.

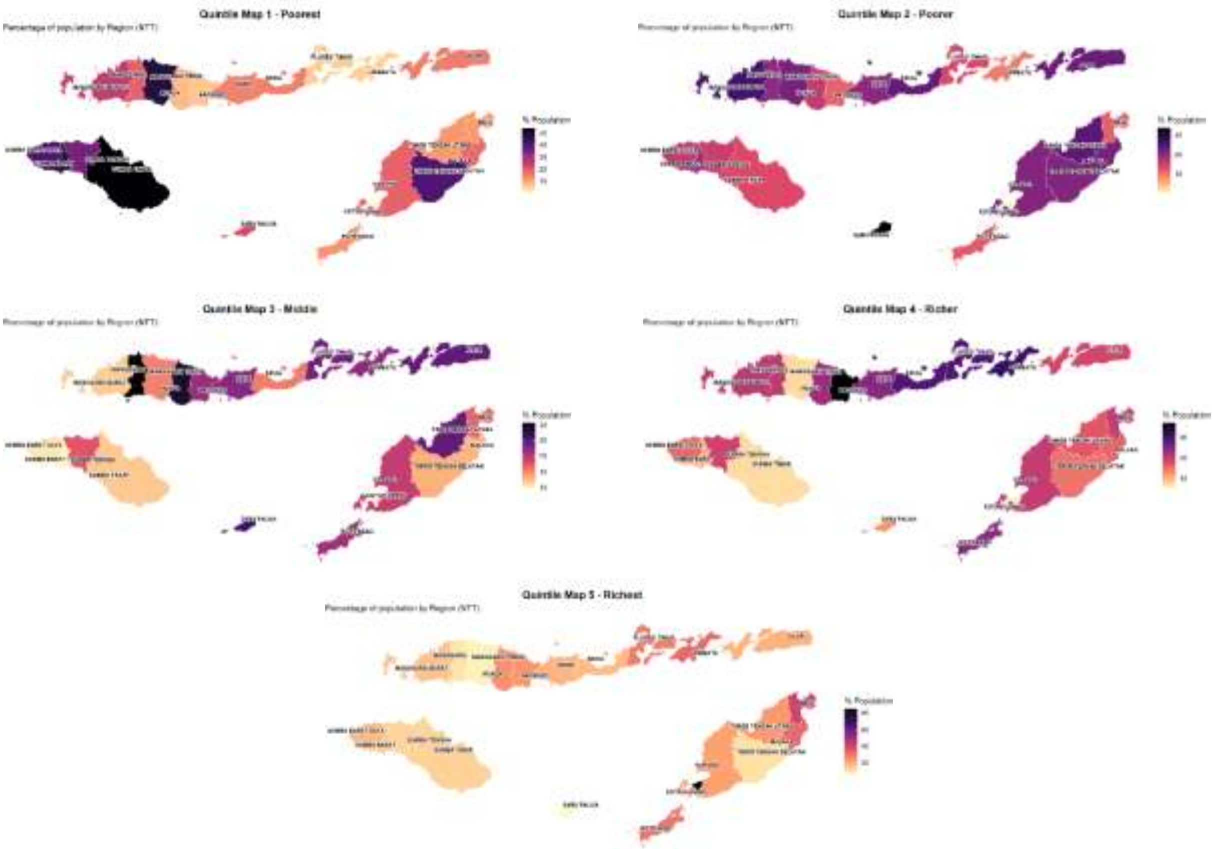

Figure 1. Population distribution in East Nusa Tenggara Province based on wealth quintiles

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

The spatial pattern in Fig. 1 confirms an extreme center-periphery divide, where welfare is concentrated in urban areas like Kupang City, while outer archipelagic regions remain underdeveloped. Areas with advanced infrastructure access and economic growth centers tend to have darker colors in the top quintiles (Q4 and Q5). Conversely, geographically isolated regions appear darker in the bottom quintiles (Q1 and Q2). This visualization provides legitimacy for policymakers to use this asset-based index as an instrument for more precise, place-based development interventions in NTT. A more detailed analysis of this disparity is presented in Table 6, which shows the percentage distribution of the population across quintiles for each district/city.

Table 6 reveals sharp regional disparities between districts. Kupang City, as the center of government and economy, shows a dominance in the upper economic strata, where 68.72% of its population is concentrated in Quintile 5 (Richest) and only 1.23% is in Quintile 1. This condition stands in stark contrast to districts in other archipelagic areas that still face serious asset deprivation challenges.

Table 6. Percentage of population distribution in each quintile for each district/city

District/City	Percentage (%)				
	Q1	Q2	Q3	Q4	Q5
SUMBA BARAT	42,55%	17,41%	11,80%	11,41%	16,83%
SUMBA TIMUR	36,89%	16,89%	12,95%	12,79%	20,49%
KUPANG	18,94%	17,27%	18,48%	23,18%	22,12%
TIMOR TENGAH SELATAN	37,54%	22,06%	13,61%	12,89%	13,90%
TIMOR TENGAH UTARA	11,17%	18,06%	23,32%	22,00%	25,45%
BELU	6,72%	16,55%	20,86%	22,93%	32,93%
ALOR	12,23%	14,74%	30,32%	24,79%	17,92%
LEMBATA	6,19%	9,47%	26,05%	29,87%	28,42%
FLORES TIMUR	3,06%	10,65%	23,87%	30,32%	32,10%
SIKKA	10,49%	18,06%	23,77%	19,14%	28,55%
ENDE	9,55%	13,54%	17,68%	30,41%	28,82%
NGADA	6,30%	13,15%	26,48%	25,19%	28,89%
MANGGARAI	16,61%	25,39%	25,71%	16,30%	15,99%
ROTE NDAO	8,24%	10,26%	20,33%	35,53%	25,64%
MANGGARAI BARAT	18,03%	20,82%	20,98%	20,33%	19,84%
SUMBA TENGAH	37,87%	17,78%	17,57%	13,60%	13,18%
SUMBA BARAT DAYA	47,57%	18,94%	12,83%	10,49%	10,17%
NAGEKEO	5,74%	12,78%	24,63%	29,63%	27,22%
MANGGARAI TIMUR	42,45%	22,89%	15,26%	9,70%	9,70%
SABU RAIJUA	22,65%	27,14%	21,63%	16,33%	12,24%
MALAKA	21,26%	19,73%	19,90%	20,41%	18,71%
KOTA KUPANG	1,23%	4,16%	6,01%	19,88%	68,72%

Source: Results of SUSENAS 2025 data analysis, processed by the researcher

Southwest Sumba (Sumba Barat Daya) is recorded as having the highest proportion of the population in Quintile 1 (Poorest), reaching 47.57%, followed by West Sumba (42.55%) and East Manggarai (42.45%). This data pattern confirms that asset wealth accumulation in NTT is highly centralized in urban areas, while rural areas on Sumba Island and parts of Flores dominate the composition of the lowest quintiles. Strategically, the stratification results from this spatial analysis provide crucial policy implications for the NTT Provincial Government. Through this mapping, the government can identify poor outliers with high asset deprivation. These areas require interventions that focus not only on income improvement but also on upgrading basic infrastructure, such as sanitation and housing quality.

CONCLUSION

This study successfully developed a robust Household Wealth Index for East Nusa Tenggara (NTT) Province using Principal Component Analysis (PCA) on 2025 SUSENAS microdata, with strong statistical validity indicated by a KMO value of 0.84 and a significant Bartlett's test ($p < 0.001$). The First Principal Component (PC1) effectively captured long-term socioeconomic status, confirming that an asset-based approach provides a more stable proxy than expenditure data. Empirical findings highlight a stark divide in asset ownership, where high-value goods (e.g., computers, cars, air conditioners) strongly differentiate wealthier households in Quintile 5, while Quintile 1 households experience severe deprivation in basic housing and sanitation; notably, land ownership shows limited discriminatory power in this agrarian context. Spatial analysis further reveals a pronounced center–periphery inequality, with welfare concentrated in urban areas such as Kupang City and persistent poverty in outer and inland regions like East Sumba and East Manggarai, underscoring the role of geographic and infrastructural constraints. These findings imply the need for targeted, place-based policy interventions, prioritizing infrastructure development in disadvantaged areas, while also demonstrating the utility of the wealth index for actuarial applications such as microinsurance design and improved social assistance targeting. Future research is recommended to incorporate longitudinal data to assess temporal dynamics of welfare mobility and to integrate geospatial and environmental variables for a more comprehensive understanding of structural inequality in archipelagic regions.

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