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A Modified Human Development Index and Poverty in the Villages of West Seram Regency, Maluku Province, Indonesia

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ABSTRACT

The first purpose of this paper is to develop or construct a new human development composite index and applied to measure the performance of human development in the villages of West Seram Regency, Maluku Province. The second, to develop the priority scale of human development for development planning. The third, analyzing the effect of HDI's indicators on poverty level. This paper applies principal component analysis (PCA), clustering analysis and panel data regression. PCA method generates index which we called Modified Human Development Index. Based on clustering analysis, the number of villages in the high cluster is 6 villages, the medium cluster is 13 villages and low cluster is 14 villages. The modified human development performance has an important role for poverty alleviation and improving the level of people's welfare in the villages. This paper also revealed empirical study that the HDI's indicators have negative relationships and significant effect on poverty rate.

Keywords: Human Development, Poverty, Principal Component Analysis, Clustering, Panel Data, Villages
JEL Classifications: C3, C4, O1, I3

1. INTRODUCTION

Nowadays, many countries including Indonesia consider human development and poverty alleviation as one of the benchmarks of development success and plays an important role in improving the level of people's welfare of a country.

Since the issuance of law number 6 of year 2014, which then followed up with government regulation number 43 of 2014 brings the implications or demands of development planning in Indonesia should start from the lowest level of government (village) that shows the seriousness and political will of the government to carry out development in a balanced and equitable. To realize these demands, optimal and effective development planning requires the availability of accurate and comprehensive data at district, sub-district and village levels. To create more equitable economic development and reduce poverty, one of the main priorities in the medium term development plan document of West Seram Regency in Maluku Province is to improve the performance of human development.

So far, the measurement of human development progress applied by official institutions in various countries refers to method developed and popularized by the United Nations Development Program (UNDP) known as Human Development Index (HDI), often published in the annual Human Development Report (HDR). The HDI has become a widely used measure for understanding patterns of socio-economic development. It was created to emphasize that people and their capabilities should be the ultimate criteria for assessing the development of a country, not economic growth alone.

Ever since the HDI was first published, it has drawn critiques from many sides. The critiques are mostly related to high correlation of HDI components, functional form of the HDI including normalization of component indicators, aggregation vs multiplication, and issues related to weighting (Kovacevic, 2010). Some critiques claim that the methods used to combine the variables into indexes are more subjective and less theoretical validity (McGillivray, 1991; Noorbakhsh, 1998). The problem is that as HDI is the average of the sum of three equally weighted indices, it follows that the absolute value of each component will affect the level of

HDI. Hence the selected extreme values would affect the value of the index resulting in a change in the ranking order (Noorbakhsh, 1998). The HDI has been criticized on the grounds of attaching equal weights to its selected components. Some researchers have argued that as an increase in income can increase people's choice and achieve improvements on other components, it should be given a higher weight (Kelly, 1991). Furthermore, McGillivray's (1991) and Srinivasan (1994) studies found that a high correlation between human development components or correlated with composite indexes would lead to statistical problems and be unable to provide accurate and comprehensive information.

Referring to a number of previous studies there are several models that have been developed for improving the measurement of human development. Kovacevic (2010); McGillivray, (2005); McGillivray and White, (1993); Lai (2003); Ogwang and Abdou, (2003) proposed a new method using principal component analysis (PCA).

Characteristics of poverty in Indonesia is marked by very high poverty disparity between regions in Indonesia where the poverty rate in Jakarta is very low, amounting to 3.75% and Maluku Province has the third highest poverty rate in Indonesia amounted to 19.18% of the total population. West Seram regency is one of the sub-districts in Maluku province with the highest poverty rate of 26.50% of the total population.

The basic objectives of the study are

1. To develop or construct a new human development composite index and applied to measure the performance of human development in the villages of West Seram Regency, Maluku Province.
2. To develop the priority scale of human development for local development planning.
3. To analyze the effect of modified human development index (MHDI) on poverty rate.
4. To analyze the effect of HDI'indicators on poverty rate.

2. LITERATURE REVIEW

In essence, the HDI is a summary measure of average achievement in key dimensions of human development: A long and healthy life, being knowledgeable and have a decent standard of living. The HDI is the geometric mean of normalized indices for each of the three dimensions. The health aspect of the HDI is measured by the life expectancy, as calculated at time of birth, in each country. Education is measured on two levels: The mean years of schooling for residents of a country and the expected years of schooling that a child has at the average age for starting school. The metric chosen to represent standard of living is GNI per capita based on purchasing power parity (PPP), a common metric used to reflect average income (HDR, 2016).

According to the World Development Bank, "poverty is pronounced deprivation in wellbeing". In other hand, poverty is multifaceted, manifested by conditions that include malnutrition, inadequate shelter, unsanitary living conditions, unsatisfactory and insufficient supplies of clean water, poor solid waste disposal, low educational achievement and the absence of quality schooling, chronic ill health, and widespread common crime(UNSD, 2005).

In a broad sense, poverty means the inability of a person to fullfil their needs in accordance with the relative perception of himself. To measure the poverty, Statistics Indonesia (BPS) uses the concept of ability to fullfil the basic needs (basic needs approach). With this approach, poverty is seen as an economic inability to fullfil the basic needs of food and non-food which is measured from the expenditure side. So the Poor is the population had an average monthly per capita expenditure below the poverty line.

There are many factors affecting poverty. The empirical study of Singh (2012) clearly revealed that HDI and per capita income have profound influence on the reduction of poverty. Effect of HDI and per capita income on poverty reduction is found significant and the impact of HDI on poverty is negative. Furthermore, study of Arief and Pratiwi (2017) concluded that HDI's indicators have negative relationships and significant effect on poverty reduction statistically.

3. DATA AND METHODOLGY

Data used is sourced from database of Development Planning Agency at Sub-National Level of West Seram Regency and also taken from Research & Economic Study Laboratory database in Economic and Business Faculty of Pattimura University, year 2015-2016.

Administratively, West Seram Regency is one of Maluku province consisting of 11 sub-districts. However, in this study only taken 6 sub-districts or 32 villages with consideration of the completeness or availability of data. For constructing a new composite index of human development, the indicators (Table 1) were processed only after standardization, in order to avoid the mistakes coming from the different units and sizes.

Beyond descriptive statistical tools the methods of PCA and cluster analysis were used in first and second research purposes. The PCA is used for compacting the information stored in the variables into few uncorrelated factors without losing too much content. This method is excellent to carry out statistical analysis in a transformed smaller dimension without wasting useful data. This method can be used efficiently if there are numerous stochastically strongly correlated variables which contain redundant information (Ketskeméty, 2005).

Cluster analysis is a multivariate statistical and data segmentation method which is suitable for grouping data into homogenous groups. The aim of cluster analysis is to class the examined cases in homogenized groups based on chosen variables. These examined cases have to be similar in one group and have to differ from the other groups (Gozali, 2013).

This paper uses panel data which is a combination of cross-section data and time series data. Cross-section data consist of 32 villages in West Seram Regency, Maluku Province while the time series data as much as 2 series, i.e., from 2015 to 2016.

The Index construction and analysis of the research will go through several steps, the following:

Table 1: Dimensions, indicators and method of analysis

Dimensions	Indicator	Method of analysis	Output
Economic	Adjusted expenditure per capita (rupiah/year)	PCA Clustering Analysis	A MHDI Cluster of Villages
Education	Mean years of schooling (years) Expected years of schooling (years)		
Health	Life Expectancy (years)		
Dependent variable	Poverty rate is measured by percentage of poor family (%)	Panel Data Regression Model	Determinant of poverty rate
Independent variables	MHDI Adjusted expenditure per capita (rupiah/year), as a proxy of income per capita Mean years of schooling (years) Life expectancy at birth (years) Dependency ratio (%)		

Source: Own Editing. PCA: Principal component analysis, MHDI: Modified human development index

First, testing sampling adequacy and correlation in PCA by using Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. This step is necessary in order to determine the suitability of data for such a method. The KMO index ranges from 0 to 1 and the sample is considered suitable for PCA if this index is equal or higher than 0.50. Also the Bartlett's Test of Sphericity should be significant ($P < 0.05$) indicating the overall significance of all correlations within a correlation matrix.

Second, construct a composite index of human development with the same component or indicator of UNDP (Table 1). However, this index does not use the UNDP method but uses the weight of the PCA and generate index. This index is called MHDI. The thumb rule/cut-off usually used to determine the selection of principal component amount is the eigenvalue value is more than 1 and the proportion of total variance ≥50% (Gozali, 2013).

The method of weighting the variables is automatically incorporated into the decision of using PCA. The first principal component is usually thought to symbolize the overall index, the eigenvector obtained for the principal component is used as the weight PCA (See for example Vyas and Kumaranyake, 2006; Lindman and Sellin, 2011).

Third, determine the influence of the human development on poverty by using the panel data regression analysis. Model 1 used to analyze the influence of MHDI on poverty with the following regression equation:

$$POV_{it}=\alpha_i+\beta_1 MHDI_{it}+\varepsilon_{it} \qquad (1)$$

Model 2 used to analyze the effect of HDI's indicators and dependency ratio on poverty level with the following regression equation:

$$POV_{it}=\alpha_i+\beta_{1+}AEP_{it+}\beta_2 MYS_{it+}\beta_3 LE_{it+}\beta_4 DCR_{it}+\varepsilon_{it} \qquad (2)$$

Where:

α_i is constant (intercept) of village i, POV_{it} is poverty rate in the village i in year t, AEP_{it} is adjusted expenditure per capita or PPP in village i, year t, MYS_{it} is mean years of schooling in the village i in year t, LE_{it} is life expectancy at birth in the village i year t, DCR_{it} is dependency ratio in the village i year t, $MHDI_{it}$ is a MHDI in the village i in year t. In the model 2, all variables are converted into natural logarithms except for poverty and dependency ratio variables because of percent measurement units.

4. RESULTS AND DISCUSS

4.1. MHDI

It has been explained previously that the purpose of the PCA is transforms data in a linear way on a correlated variable into a new data structure with new variables (referred to as the main components) that are not mutually correlated. The first step is to test the sample feasibility and the variables that will be used for the analysis of the main components by using KMO and Barlett's Test of Sphericity shown in the following Table 2:

The KMO index ranges from 0 to 1 and the sample is considered suitable for PCA if this index is equal or higher than 0.50. Also the Bartlett's Test of Sphericity should be significant ($P < 0.05$). It can be concluded that the strength of the relationship among variables is strong or the correlation matrix is not an identity matrix as is required by factor analysis to be valid. These diagnostic procedures is presented of Table 2 indicate that factor analysis is appropriate for the data.

After these tests we have to take a decision regarding the number of factors (principal components) that should be retained in the model. In the initial solution the number of components is equal to the number of variables included in the model (Table 3). Every component has an eigenvalue which represents the amount of variance that is accounted for a given component. Usually the first variables have the greatest eigenvalues. One of the most commonly used criteria for principal component selection is the Kaiser's criterion known also as eigenvalue-one criterion. According to this one only the variables with the eigenvalue <1 will be retained in model. Using of eigenvalue-one criterion is not considered the best decision when the actual differences between the eigenvalues of successive variables are quite small. Thus a variable with an eigenvalue of 0.99 will be excluded from the model in spite of its significant contribution to the total variance. For these reason, the proportion of variance accounted for by every factor and the cumulative percentage of variance could be used in the process of factor selection.

In Table 3 we can see that only the first components have the eigenvalue >1 and it explains 70.39% of the total variance. Therefore only the first factor can be used for constructing HDI.

It is interesting to note that all four components of MHDI, the adjusted expenditure per capita (AEP), mean years of schooling (MYS), expected years of schooling (EYS) and life expectancy (LE) have very high loadings on factor 1. This factor with an eigenvalue of 2.816 accounts for almost 70.4% of the total variance while the remaining three factors with eigenvalues of 0.786, 0.259 and 0.140 account for around 20%, 6.5% and 3.5% of the total variance respectively.

The loadings themselves are the correlations between the components and factors. All components have high correlations with factor 1 resulting in rather high coefficients of determination between them and factor 1. The high loadings of these components on factor 1 suggest that the equal weighting of the components is not very inappropriate. In a way this factor may be interpreted as the factor of human development as explained by four components. As factor 1 accounts for a very high proportion of total variance it is possible to argue that it is by far the most dominant factor. It is then possible to compute the so-called factor scores for all villages on the basis of this dominant factor.

From the estimation results obtained weight value of each variable. The size of the variable weights is determined by the value of the eigenvector or component score coefficient value so that new equations are formed to form the new composite index of human development as follows:

$$IC_1=0.407AEP+0.538MYS+0.512EYS+0.512EYS \quad (3)$$

As a first step in the computation of a single index, factor score coefficients, also called component scores were estimated using regression method. Factor scores are the scores of each case, on each factor. To compute the factor scores for a given case for a given factor, the case's standardized score on each variable is multiplied by the corresponding factor loading of the variable for the given factor, and summed these products. This calculation was carried out using SPSS procedure and factor scores were saved as variables in subsequent calculations involving factor scores (Vyas and Kumaranayake, 2006).

The value of the index can be positive or negative, making it difficult to interpret. Therefore, a Standardized HDI was developed, the value of which can range from 0 to 100, using the following formula:

$$NV\ (i)=\frac{(Value\ (i)\text{-}Min\ V)}{(Max\ V\ \text{-}\ Min\ V)}x100 \quad (4)$$

A similar procedure was adopted in previous research (Krishnan, 2010; Antony and Rao, 2007; Ariawan, 2006). The scores were later reversed to make the interpretation easier; the higher the value, the better human development progress.

The procedure using PCA of this step generates these scores index which we called MHD1. The composite index of MHDI are shown in Table 4 together with the HDR ranks that are based on the HDI UNDP (using equal weights).

4.2. Rank, Cluster and Priority Scale of Villages

In the next stage will be clustering, using composite index data obtained from the PCA. The use of this analysis aims to classify villages according to performance or achievement of MHDI. Based on the Clustering Analysis results, there are 3 main clusters of high, medium and low cluster. The high cluster is 6 (six) villages, with an average composite index of 92.70. The medium cluster is comprised of 14 villages, with an average composite index of 58.64. The low cluster amounted to 12 villages, with an average composite index of 6.27 Table 5.

4.3. Panel Data Regression

In the panel data regression, there are several steps that must be done, ie select the estimation model, determine the estimation method, assumptions testing and goodness of fit test. On the panel data regression analysis, the estimation model generally three approaches. There are Common effect Model (Ordinary Least Square, OLS), fixed effect model and the random effect model. Among the three techniques, the chosen approaches whether the Common Effects Model, Fixed Effects Model (FEM) or REM will be determined through a Chow test, LM test and Hausman test (Baltagi, 2005; Gujarati, 2004).

Next, conduct appropriate formal test to examine individual group and/or time effects. If the null hypothesis of the LM test is rejected, a random effect model is better than the pooled model. If the null hypothesis of the F-test is rejected, a fixed effect model is favored over pooled model. If both hypothesis are not rejected, fit the pooled model. Conduct the Hausman test when both hypothesis of the F-test and LM test are all rejected. If the null hypothesis

Table 2: KMO dan Barlett's Test of Sphericity

KMO	0.679
Barlett's Test of Sphericity:	
Approx. Chi-square	72.661
Degree of freedom (df)	6
P (α=5%)	<0.0001

Source: Authors' Own Computation. KMO: Kaiser Meyer Olkin

Table 3: Eigenvalue and Factor Selection

Indicator of PCA	PC1	PC2	PC3	PC4
Eigenvalue	2.816	0.786	0.259	0.140
Variability (%)	70.391	19.638	6.471	3.501
Cumulative%	70.391	90.028	96.499	100.00

Source: Authors' Own Computation. PCA: Principal component analysis

Table 4: LF, EVR and Weight of MHDI

Variable	LF	EVR	Weight
AEP	0.682	0.407	0.407
MYS	0.903	0.538	0.538
EYS	0.858	0.512	0.512
LE	0.893	0.532	0.532

Source: Authors' Own Computation. LF Loading factor, EVR: Eigenvector, AEP: Adjusted expenditure percapita, MYS: Mean years of schooling, EYS: Expected years of schooling, LE: Life expectancy, MHDI: Modified human development index of uncorrelation between an individual effect and regressors is rejected, go for the robust fixed effect model, otherwise, stick to the efficient random effect model (Park, 2011).

In model 1, the best model chosen in the statistical test is FEM and in model 2 the best model chosen of the statistical test is common effect model (pooled least squared or OLS). Summary of panel data regression output listed in Table 6.

Based on Table 6, we get the information that the human development has influence on poverty reduction in the villages of West Seram Regency. This information is reflected on both models. Model 1 used to analyze the influence of MHDI on poverty. Table shows that adjusted R-squared is 0.9989. This result implies that on the average about 99.89% of variance in poverty is explained by changes in HDI. This model also have probability value of <5% simultaneously (F-statistic = 0.000). This output indicates that MHDI have influence

Table 5: Rank Comparison of HDI-UNDP and MHDI, Cluster and Scale Priority of Villages in West Seram Regency, Year 2016

Sub-districts	Villages	HDI-UNDP	Rank	MHDI	Rank	Rank Difference	Cluster	Scale of Priority
Kairatu Barat	Kamal	65.96	1	100.00	1	0	High	3
Kairatu	Kairatu	65.94	2	97.32	2	0	High	3
Kairatu Barat	Waesamu	65.94	3	97.32	3	0	High	3
Kairatu	Waimital	65.77	4	91.37	4	0	High	3
Kairatu Barat	Waipirit	65.72	5	89.67	5	0	High	3
Kairatu	Seruawan	65.34	6	80.53	6	0	High	3
Kairatu Barat	Uraur	64.92	7	70.38	8	1	Medium	2
Kairatu	Hatusua	64.87	8	69.04	9	1	Medium	2
Kairatu	Kamarian	64.76	9	67.68	11	2	Medium	2
Kairatu Barat	Waisarisa	64.55	10	71.44	7	3	Medium	2
Kairatu	Latu	64.12	11	64.03	12	1	Medium	2
Amalatu	Tehulale	64.12	12	64.03	13	1	Medium	2
Amalatu	Rumahkay	64.10	13	63.79	14	1	Medium	2
Amalatu	Hualoy	64.08	14	62.74	16	2	Medium	2
Amalatu	Tomalehu	64.07	15	62.92	15	0	Medium	2
Amalatu	Waihatu	63.38	16	68.51	10	6	Medium	2
Kairatu Barat	Elpaputih	63.18	17	33.84	20	3	Medium	2
Amalatu	Lohiatala	62.98	18	43.80	17	`1	Medium	2
Amalatu	Tala	62.81	19	39.14	19	0	Medium	2
Elapaputih	Seriholo	62.76	20	39.60	18	2	Medium	2
Kairatu Barat	Hunitetu	62.03	21	6.67	27	5	Low	1
Elpaputih	Ahiolo	62.01	22	8.43	22	0	Low	1
Elpaputih	Sumeith Pasinaru	61.97	23	7.42	24	1	Low	1
Elpaputih	Nurue	61.93	24	20.59	21	3	Low	1
Elpaputih	Watui	61.93	25	7.53	23	2	Low	1
Elpaputih	Wasia*	61.93	26	6.83	26	0	Low	1
Inamosol	Sanahu*	61.93	27	6.84	25	2	Low	1
Elpaputih	Huku Kecil	61.92	28	6.63	28	0	Low	1
Inamosol	Hukuanakota	61.88	29	1.48	30	1	Low	1
Inamasol	Rumberu	61.85	30	1.55	29	1	Low	1
Inamosol	Manusa	61.84	31	1.24	31	0	Low	1
Inamasol	Rambatu	61.80	32	0.00	32	0	Low	1

Source: Authors' Own Computation. Cluster analysis based on MHDI. MHDI: Modified human development index, HDI- UNDP: United Nations Development Program-Human Development Index

Table 6: Summary of output panel data regression

Dependent Variable: POV? (Model 1)								
Variable	Coefficient	Standard error	t-test		F-test		R-squared	D-W Stat
			t-stat	P	F-stat	P		
Constanta	−0.000469	0.002878	−11.99121	−0.16313	3653.236	0,00000	0.99889	3.878788
MHDI?	−4.623998	1.289349	−3.586304	0.0011				
Dependent variable : POV? (Model 2)								
Variables	**Coefficient**	**Standard Error**	**t-test**		**F-test**		**R-Squared**	**D-W Stat**
			t-stat	**P**	**F-stat**	**P**		
Constanta	37.76900	8.538564	4.423343	0.0000	71.54080	0,00000	0.829066	1.744738
AEP	−2.116222	0.547135	−3.867822	0.0003				
MYS	−1.727040	0.169142	−10.21060	0,0000				
LE	−0.767099	0.087281	−8.788890	0.0000				
DCR	2.194660	0.362990	6.046061	0.0000				

Source: Authors' Own Computation. Amount of observation is 64 and all statistic test using significance level of 5%. AEP: Adjusted expenditure percapita, MYS: Mean years of schooling, EYS: Expected years of schooling, LE: Life expectancy on poverty statistically. The regression result also shows that the impact of HDI on poverty is negative. That result showed by coefficient of HDI is −4.62. The results given on model 1 state that, if MAHDI increases by 1%, poverty decreases by about 4.62%.

Model 2 used to analyze the effect of HDI's indicators (AEP, MYS, LE) and DCR on poverty. Table shows that adjusted R-squared is 0.829066. This result implies that on the average about 82.91% of variance in poverty is explained by changes in HDI's indicators and dependency ratio (DCR). This model also has probability value of <5% simultaneously (F-statistic = 0.000). This output indicates that HDI's indicators and dependency ratio have influence on poverty statistically.

If seen partially, all variables have influence on poverty at 95% confidence level. The regression result also shows that the impact all of HDI's indicators on poverty are negative and dependency ratio variable has a positive relationships. That table show that coefficient of AEP, MYS, LE and DCR respectively is −2.12; −1.73; −0.77 and 2.19. The result given in model 2 implies that, if AEP increases by 1%, poverty decreases approximately 2.12%; if MYS increases is 1%, poverty decreases about 1.73%; if LE increases is 1%, poverty decreases about 0.77% and if DCR increases by 1%, poverty increases about 2.99%, ceteris paribus.

These results are conform with the study Hidayat (2008), Arief and Prastiwi (2017) which reveal that increasing the human development can be decreasing the poverty.

5. CONCLUSION AND RECOMMENDATION

Composite index compositions resulting from MHDI and HDI-UNDP largely result in different ranking information but in some villages have the same rank. Based on K-means clustering analysis, there were 3 main clusters, namely high, medium and low cluster. The number of villages in the high cluster is 6 villages, the medium cluster is 13 villages and low cluster is 14 villages.

The output of panel data analysis indicates that HDI's indicators and dependency ratio have influence on poverty statistically. Partially, all variables have influence on poverty at 95% confidence level. The regression result also shows that the impact all of HDI's indicators on poverty are negative and dependency ratio variable has a positive relationships.

The human development has an important role for poverty alleviation and improving the level of people's welfare in the villages of West Seram Regency. The political will of local government to improve human development is one of key success for poverty reduction. The improvement of human development performance can be implemented through greater attention to human development particularly by increasing budgetary and plan expenditure on social sector and generation of adequate employment opportunities.

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