

POVERTY MAPPING: AN EFFECTIVE APPROACH IN DETERMINING THE POOR AREA – CASE STUDY OF JOHOR

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Abstract

Poverty reduction has become a major concern to the Government especially in achieving the target of the Millennium Development Goals (MDG) to reduce poverty from 3.7 per cent in 2007 to 2.5 per cent by the year 2010. The poverty rates at the national and state levels are obtained from the Household Income Survey (HIS). There is a need to estimate the poverty rate at a smaller area such as districts and “mukim” (sub-districts) to identify the pockets of poverty. Therefore, poverty mapping is adopted for this purpose based on the HIS and the Population & Housing Census. The regression technique is used to get the estimated parameter coefficient from the HIS and it is simulated to the census data. This paper presents the findings of the pilot study for the state of Johor.

Keywords: Poverty mapping, Small Area Estimation (SAE)

Introduction

Poverty reduction has become the most important issue of almost all countries around the world. The United Nations through its General Assembly (UNGA) has started the effort to formulate the Millennium Declaration since 1998. Finally, in September 2000, the UNGA, represented 189 countries, unanimously adopted the Millennium Declaration which consist of eight goals, 18 targets and 48 indicators which is known as the Millennium Development Goals (MDGs). One of the goals is to eradicate extreme poverty and hunger. The target of this goal is to halve the poverty rate in the period of 1990 to 2015 that is the proportion of people whose income is less than USD1 a day. The second target is to halve the proportion of people who suffer from hunger between 1990 and 2015.

In Malaysia, the poverty eradication programmes have resulted in drastic reduction in poverty and lessened the income inequality while achieving rapid economic growth and maintaining racial harmony. Malaysia has formulated a range of policies and plans to guide the management of national development during 1970s. The New Economic Policy (NEP), 1970 – 1990 and subsequent policies have markedly reduced poverty. The success of Malaysia’s poverty eradication programmes is evidenced by the sharp decline in the incidence of poverty, which decreased from 52.4 per cent in 1970 to 12.4 per cent in 1992 and further decreased to 3.8 percent in 2009.

The poverty eradication programme is a continuous effort as poverty is a multidimensional issue. Thus, in 2009, the government has launched the

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Government Transformation Program (GTP) which comprised of six National Key Results Areas (NKRA). One of the key areas is to raise living standards of low-income households. The target of this NKRA is to reduce the extreme hardcore poor households to zero and also to halve the number of the poor households. With the concern of the government to reduce poverty, the smaller area poverty statistics comes to fore. A major problem at present is reaching out to the poor to address their specific needs, which calls for poverty statistics at the smaller level of geographic disaggregation: state, district and *Mukim*. To identify the poor and their needs, data on their social conditions are important.

Currently, the poverty rate is calculated at the national, state and stratum levels using the HIS which is conducted twice in 5 years. Poverty mapping requires detailed data on population distributions at small areas. The availability of population census data enables poverty mapping at district and sub district levels. This paper elaborates the results of poverty mapping in Johor. This state was selected in the pilot study due to its importance as the pioneer state in the Southern Economic Corridor as well as having one of the lowest poverty rates in Malaysia. Besides, it is important for the Department to study the robustness of the poverty mapping methodology and hence develop a comprehensive plan to construct poverty maps for Malaysia. Finally, through this poverty mapping approach, the government will be able to identify the poor households as well as their locations.

Literature Review

Over the last thirty years, there has been growing demand for reliable estimates for small domains for which only a few, or no sample data are available. Examples include estimates of unemployment rates in local authority districts, estimates of disease prevalence for small demographic groups, and poverty mapping. Interest in small area estimation has been further stimulated by the fact that many European countries are now basing their censuses on administrative records. The inaccuracies of the administrative data and the fact that even the richest records cannot cover all the detailed information required for small census tracts lead to the need to test, correct and supplement the administrative information by sample data.

The small-area estimation is a statistical technique that combines survey and census data to estimate welfare or other indicators for disaggregated geographical units such as municipalities or rural communities. The small-area estimation applies parameters from a predictive model to identical variables in a census or auxiliary database; the assumption is that the relationship defined by the model holds for the larger population as well as the original sample. This technique has been used by the United States government for planning and targeting purposes (Ghosh and Rao, 1994).

The small-area estimation has more recently been extended to developing countries for poverty mapping. Two principal methods have emerged. The first method uses census data on household units. It was developed principally by staff at the World Bank and is the main methodology used and promoted by the Bank's new poverty-mapping group (World Bank, 2000). The second method uses community-level averages instead of data on household units and has been employed by researchers

at the World Bank and various centres of the CGIAR (Consultative Group on International Agricultural Research) system. These econometric models are not causal: they do not seek to explain the determinants of poverty, but maximize precision in identifying the poor. This is an important distinction in terms of the kinds of explanatory variables that are utilized.

Poverty mapping is the spatial representation and analysis of indicators of human well-being and poverty (Henninger and Snel). They do not only provide the means by which social and economic indicators can be integrated but also the vehicle whereby biophysical information can be presented. Thus, poverty maps provide a systematic and analytical picture of poverty. In several countries in Africa, Asia and Latin America, poverty maps have been widely used in their fight against poverty.

Poverty map has become more popular due to many reasons. It is a powerful tool for visualising the location and describing the conditions of the poor. Poverty maps also help in identifying priority areas and how to target anti-poverty programmes and can be vital tools for empowering the local populace to actively participate in the identification and conceptualisation of anti-poverty initiatives. Identifying spatial patterns with poverty maps can provide insights in the reasons affecting specific aspects of poverty.

Poverty map makes possible the integration of data from various sources such as surveys and administrative-based data and from different disciplines such as social, economic and environmental data. Thus, different dimensions of well being can be examined and integrated. Generally, the poverty mapping process begins with the nationally representative household survey, such as Living Standard Measurement Survey (LSMS), to acquire a reliable estimate of household expenditure (y) and calculate more specific poverty measures linked to poverty line. A common set of explanatory variables x (e.g. educational background, household characteristics and quality of housing) at the household-unit level in both the survey and the census. These common variables are then used to estimate the statistical relationship between y and x in the survey. Once a robust model has been identified for the survey, the researchers apply the final model to the census data at household-unit level to predict per capita household expenditures (including an error estimate). These household unit data can then be aggregated to small statistical area, such as districts to obtain more robust estimates of the percentage of household living below the poverty line. Then, these poverty rates by administrative area are linked to a mapping programme to produce poverty map showing the spatial distribution of poverty.

Initially, there are two methods that could be applied while constructing the poverty mapping through SAE. The first method is household-level method which used the census data on household units. It was developed principally by staff at the World Bank and is the main methodology used and promoted by the Bank's new poverty-mapping group (World Bank, 2000). This method requires a minimum of two sets of data; household-level census data and representative household survey corresponding approximately to the same period as census. In Nicaragua, for example, poverty maps have been made by using data from a 1995 population census and a 1998 Living Standards Measurement Study (LSMS) survey. In Ecuador, data from a 1990 population census were used with 1994 survey data. The

maximum allowable time difference will vary by the rate of economic change in the given country. Beside a population census data, other sufficiently representative large-scale survey that includes basic demographic information also could be used. Elbers *et. al* (2001) provides an example of small-area estimation in Brazil using a large-scale household survey instead of a population census. This has the advantages that data requirements are less stringent and national statistical agencies may be more likely to release community averages on request; indeed, this data may be published.

The poverty mapping was widely tested and successfully used in providing the small area statistics. The World Bank encouraged the usage of poverty mapping as a tool for poverty eradication especially in the developing countries. In ASEAN region, most of the countries have already started developing their own poverty maps. For example, Indonesia started its pilot project since midst 1990s. Using data from three pilot provinces, the study has successfully calculated various poverty and inequality indicators at the provincial, district and sub-district levels with reasonably acceptable standard errors. Since 2004, the national poverty map which was developed by the *Badan Pusat Statistik* (BPS) Indonesia has been used in various applications by government agencies, donors and non-governmental organisations (NGOs). For instance, in 2005, the Indonesia government has decided to cut fuel subsidies which resulted in fuel price increased. This situation would particularly affected the poor and the government has planned to absorb the negative impact by providing unconditional cash transfer to the poor. The Ministry of Finance (Indonesia) in order to ensure the programme is success had used the poverty maps to estimate the budget needed for the cash transfers.

Many countries collect information on income in population censuses. This information, typically based on only one or a few questions about cash income, has been used to create disaggregated poverty maps, without data from other sources. The Brazilian hunger map, for example, is based on direct measurement of household income reported in the 1991 population census. The household income was compared to a food-based extreme poverty line and a non-food moderate poverty line. The headcount index was then calculated for each municipality. Regional and state measures were based on a 1990 household survey (Peliano, 1993). Similar exercises have been conducted in South Africa and elsewhere. Some studies use direct measurement of census-based household income in multivariate analysis. Osgood and Lipper (2001), for example, link sub-national proxies for poverty with soil-degradation measures in Ghana.

However, recent analysis of South African data (Alderman *et al.*, 2000) shows that census income variables, which are necessarily limited, given the extremely large number of observations collected, are systematically biased. The census income data under-represent levels of well-being as compared to expenditure data from a nationwide household survey, thus giving higher rates of poverty, almost 80 per cent in this case. The differences were correlated with urban/rural location, suggesting that for rural households with a higher share of non-cash income, well-being is under-represented by census data. The census income data are thus a poor targeting tool in countries with a large share of non-monetary or informal income.

In Malaysia, the poverty eradication has become the important agenda for the government by trying to improve on the poverty targets set through the Millennium Development Goals (MDGs). The Ninth Malaysia Plan, 2006–2010, repeated the commitment to achieve growth with distribution and set targets of reducing the overall poverty rate to 2.8 per cent and eradicating hard-core poverty by 2010. It also set ambitious targets to narrow income disparities and improve equity. In 2007, the government has developed the eKasih system which contained the complete information of the poor family nationwide.

Generally, the *Sistem Maklumat Kemiskinan Negara* or *eKasih* is a database system which contains the information of the poor family for the whole nation. The objective of the system is to help the government in planning, implementing and monitoring the poverty eradication programme. As at 14 January 2011, there were 67,033 (0.82 percent) households registered as poor in the eKasih database. The information from eKasih will be used as a base for providing aids or projects' involvement which programmed for the poor family. The issues of poverty reduction become crucial as the government's target to achieve the high income country by 2020.

Data Sources

The small area estimation (SAE) of poverty uses two data sources that are the Population and Housing Census (Census) and the Household Income Survey (HIS). The Census provides information on the population at district levels while the information on income of the households is obtained from the HIS. The components of income comprise earnings from paid employment (gross income²), incomes from self-employment, property incomes, current transfer receipts and other incomes.

The Poverty Line Income (PLI) is an indicator derived from HIS for measuring the incidence of poverty. In 2005, the government has introduced the new methodology for calculating the PLI. In the new methodology, a PLI is defined separately for each household. Each household's PLI reflects:

- i) The household's size and demographic composition

Larger households require more food and non-food expenditures to achieve a satisfactory standard of living for all its members. This was due to the caloric requirements varying by sex and age, therefore the food PLI will vary with the demographic composition of the household.

- ii) The household's location: state and stratum (urban/rural)

Food and non-food prices vary significantly across the state and between urban and rural areas. For example prices in Kuala Lumpur are usually higher than elsewhere. The new PLI takes into account of these price variations.

² Gross income includes wages and salaries, cash allowances, bonuses, commissions, overtime payments, free food, free or concession lodging, free or concession consumer goods, payments in kinds and employer's contributions to EPF/SOCSO.

The total PLI is a combination of two components which are food PLI and non-food PLI. The food PLI component is based on the advice of nutritionists, dieticians and medical professionals from Ministry of Health, Universiti Kebangsaan Malaysia and Universiti Putra Malaysia. The kilo calories that are needed by a family of five persons are 8,725 per day. The Individuals daily kilo calorie requirements are met through a balanced diet which includes: cereals and cereals products (uncooked rice, wheat flour); chicken, eggs and fish; milk; oil and pats; sugar; vegetables and fruits; and pulses. The kilo calorie requirements are then converted to monetary value using the retail prices at each locality.

The non-food component is determined by the spending pattern of low income households in the Household Expenditure Survey. The non-food items are: clothing and footwear; gross rent, fuel and power; durables (furniture, furnishings and household equipment and operation); transport and communication; and other non-food items. A household is considered poor if the income is less than its own PLI. Otherwise, the household is considered hardcore poor if its income is less than its own food PLI.

The income information derived from HIS is to cater for indicators at the national, state and stratum levels. Therefore, in estimating the small areas statistics data from HIS will be mapped to the population census data that provides full counts of the population at district and sub district levels. Although the initial intention was to estimate poverty at sub district level, the efforts require massive process and detailed information which involve large resources. Thus, taking into consideration of timeliness and the complexity of the analysis, this paper will only presented the poverty map at district level only.

Methodology

The basic idea of the SAE is to combine household and census data using statistical procedure which aimed at taking advantage of the detailed information available in household sample surveys and the comprehensive coverage of a census. Thus, SAE uses a household survey to impute missing information in the census such as poverty and inequality indicator. These indicators will be estimated at a disaggregated level based on the household per capita measure of income. The SAE method used in this poverty mapping estimation can be divided into three stages (zero, first and second).

Zero Stage

The zero stage involved the identification of common variables from the survey and census datasets. To ensure that the variables are defined in the same way in two data sources, careful examination of those questions and responses is required. In the zero stage, variables within the census and household surveys are examined in great details. The objective of this stage is to determine whether the variables are statistically similarly distributed over the population census and the household survey. Creating a common variable sometimes requires collapsing of information from one or both datasets based on the statistical comparability test to ensure survey averages do not significantly differ from census means. Per capita income,

poverty lines and sampling weights should be chosen from the household survey for the preparation of income modeling.

a) Identification of data sources and common variables

Based on the SAE approach, the ideal difference of years between census and survey should not be more than five years. However, the five years difference is not compulsory as other factors such as the availability of data and the cost of conducting new census or survey should be taken into consideration. Thus, in this case study, the data from the HIS 2007 and Census 2000 was used to produce the small area of poverty estimation. Even though the time gap between the two data sources is seven years, the latest HIS information prevails.

However, by using the latest Population and Housing Census data which was conducted in 2010, the result of the SAE is probably better as the difference is only three years. The Census 2010 data is most likely ready by 2012 or 2013.

As an important part in the poverty mapping process, the common variables have to be identified in both the census and survey data set. The common variables should have the same information which adopted the same definitions, concepts, codes and classifications. Hence, the supporting documents such as the questionnaires and related manuals are very useful. The common variables that have been identified for both data sets are housing, demographic characteristics of the households' heads and amenities available in the households.

b) Data preparation

It is important to ensure that all of the census and survey data will be used in generating small area statistics. However, in order to make sure that the analysis of 26 million records in Census 2000 going smoothly, the poverty mapping will be done in stages by state. Therefore, in this case study Johor has been selected based on these criteria:

- i) Johor is the pioneer state where the economic corridor was initiated;
- ii) the incidence of poverty is relatively low as compared to the northern and eastern states;
- iii) the population of Johor was 2.5 million (696,759 households), a reasonable number for this study;
- iv) main gateway for economics activities in the Southern part of Peninsular Malaysia; and
- v) significant amount of income obtained from working abroad.

The final part in zero stage is the preparation of the final data set for both census and survey. The final data sets should consist of the identified common variables and any discrepancies of the data should be avoided. Both the census and survey data should eliminate the element of noise. Thus, the final census data set contained only 570,918 households and only 3,854 household in HIS survey. As the result, a total of 80 variables have been selected and these variables have been categorised in three criteria as follows:

- i) Housing;
- ii) Demographic particulars of the head of household; and
- iii) Amenities in the household.

Since small area estimation is the process for estimation at small domain, the high degree of comparability of the variables is crucial. In this step, the understanding of the statistical technique is important. These common variables will be tested using the hypothesis testing technique. The mean, variance, proportion and distribution of the variables will also be analysed.

The First Stage

The focus of modeling in SAE is to use the relationship between the population of interest and explanatory variables to get the best predictor for each small area.

The first stage of estimation involves modeling per capita income at the lowest geographic level for which the survey is representative. In this stage, a cross-section logarithmic regression model of per capita household income is developed and estimated on a set of variables in the household survey dataset, provided these explanatory variables also exist in the census data. Consequently, these matching variables have been statistically identified as common variables which could be used in further poverty mapping process. For example, the variables are as follows:

- i) Type of housing;
- ii) Ownership of the housing
- iii) Construction material of the household;
- iv) Type of toilets;
- v) Sex;
- vi) Age;
- vii) Marital status; and
- viii) Household appliances such as motorcar, washing machine etc.

The logarithmic income model is:

$$\ln y_{ch} = X_{ch}\beta + \mu_{ch} = X_{ch}\beta + \eta_{ch} + \varepsilon_{ch}$$

Where

c is the subscript for the cluster

h is the subscript for the household

$\ln y_{ch}$ is the log per capita household income

X_{ch} is the set of explanatory variables in the household

β is the estimated regression coefficients giving the effects of X variables on y

μ_{ch} is the disturbance (residual) term which is the sum of common (cluster)

component η_c and idiosyncratic (household) component ε_{ch}

Explicit treatment of location or cluster effect in the consumption model is important. Not accounting for them would not only bias the point estimates of poverty or inequality indicator but also inflate the standard errors, a measure of precision of the estimates. Many of the unobserved neighbourhood and geographic effects not measured by household level variables are possibly captured by the inclusion of location variables in the model.

Modeling heteroscedasticity (non-constant variance of household specific error ε_{ch} across household) helps to correctly specify the error term and involves finding a restricted number of variables (z) the best explain the variation in this error term.

ELL (Elbers, Lanjouw and Lanjouw) has proposed the following logistic model of the variance of ε_{ch} conditional on z_{ch} bounding the prediction between zero and a maximum, A, set equal to $(1.05) \cdot \max \{e^2_{ch}\}$:

$$\ln \left(\frac{e^2_{ch}}{A - e^2_{ch}} \right) = Z_{ch} \alpha + r_{ch}$$

In this stage, the common variables which have been chosen in the zero stage will be tested again using the regression technique. Thus, the model with the highest R-Square will be selected.

The Second Stage

The second stage uses the information from zero stage and first stage. This stage applies estimated parameters from alpha and beta models and empirical distribution of cluster errors and household residuals to census variables to generate predicted income for each census households.

The predicted income model for each bootstrap simulation R is

$$\hat{y}_{ch}^R = \exp (X_{ch} \tilde{\beta}^R + \tilde{\eta}_{ch}^R + \tilde{\varepsilon}_{ch}^R)$$

where

- $\hat{y}_{ch}^R$ is the simulated value of income for household h in cluster c
- X_{ch} is the census household characteristics
- $\tilde{\beta}^R$ is the coefficients drawn from the multivariate normal distribution described by the first stage parameter estimates
- $\tilde{\eta}_{ch}^R$ is the cluster level residuals drawn from the empirical distribution of $\hat{\eta}_{ch}$
- $\tilde{\varepsilon}_{ch}^R$ is household level residuals drawn from the empirical distribution of ε_{ch}

For each simulation R , a set of $\tilde{\beta}$ and $\tilde{\alpha}$ coefficients are drawn from multivariate normal distribution while making use of first stage parameter estimates and their associated variance-covariance matrices. Once $\tilde{\alpha}^R$ is drawn, variance of household residuals $\sigma_{\varepsilon, ch}^{2R}$ is estimated for each census household. Next, location (cluster) and household error term are drawn. Location error $\tilde{\eta}_c^R$ is drawn from the empirical distribution of $\hat{\eta}_c$ while $\tilde{\varepsilon}_{ch}^R$ is computed based on the parameters drawn from the empirical distribution of $\hat{\varepsilon}_{ch}$ and computed census household error $\sigma_{\varepsilon, ch}^{2R}$.

The second stage involved generating the result using the predicted parameters which have been identified in the first stage. The best estimated value derived from this stage has to be the closest to the official result of the state's poverty incidence.

Results

The poverty indicators calculated in this study were the poverty headcount index (P_0) and poverty gap (P_1). The precision of these two indicators was measured using the standard errors. In order to produce the indicators using the logarithmic income model, a total of 116 variables from HIS were initially considered. The results generated 80 models using the stepwise regressions technique, whereby the best model with the highest R^2 (0.4218) is as follows:

$$\ln y_{ch} = X_{ch}\beta + \mu_{ch} = X_{ch}\beta + \eta_{ch} + \varepsilon_{ch}$$

The coefficients of the X s were applied to the values of the corresponding variables in the census data set using the bootstrap simulation R ,

$$\hat{y}_{ch}^R = \exp(X_{ch}\tilde{\beta}^R + \tilde{\eta}_{ch}^R + \tilde{\varepsilon}_{ch}^R)$$

and a total of 100 simulations were made to estimate the $\hat{y}$ (log of per capita income). The results of the SAE poverty estimates at the district level of Johor were then compared with the results from the HIS as shown in Table 1.

Table 1: Poverty Rate and RSE using SAE and HIS, Johor, 1999 and 2007

(%)

Year	SAE		HIS	
	Poverty Rate	RSE	Poverty Rate	RSE
1999	3.9	8.5	3.1	8.9
2007	3.9	8.5	1.5	12.8

In Malaysia, the poverty line income (PLI) was calculated for each household based on basic needs which cover food and non-food components. Non-food component mainly comprises of housing, clothing and transportation. This basic need is

translated to PLI of RM696.00 per month in 2007 while the 1999's PLI was RM693.00 per month for state of Johor. A household is considered poor if its income is less than its own PLI meanwhile a household is considered hard core poor if its income is less than its own food PLI. In order to simplify the analysis, the mean PLI for the state of Johor is used as reference for comparison to other states.

Observing from the data shown in Table 1, the poverty rate is seen as more accurate if both data sources are collected within a closer time period. HIS 1999 applied to census 2000, depicted closer result than the HIS 2007 applied to same census data as shown by poverty rates of 3.9 and 3.1 respectively. Furthermore, the RSE for HIS 1999 and SAE were closer as compared to 2007. The wider the gap of the data collection for both sources, the higher the difference of the poverty rates obtained. Poverty rate of Johor using SAE was estimated at 3.9 per cent which is higher than the HIS figure (1.5%). This difference was acceptable as there was a gap of seven years between the HIS and Census 2000 data. The RSE obtained for SAE was lower compared to HIS (12.8%) as it covered the total population of Johor.

Table 2: Poverty Rate and RSE using SAE, Johor, 2007

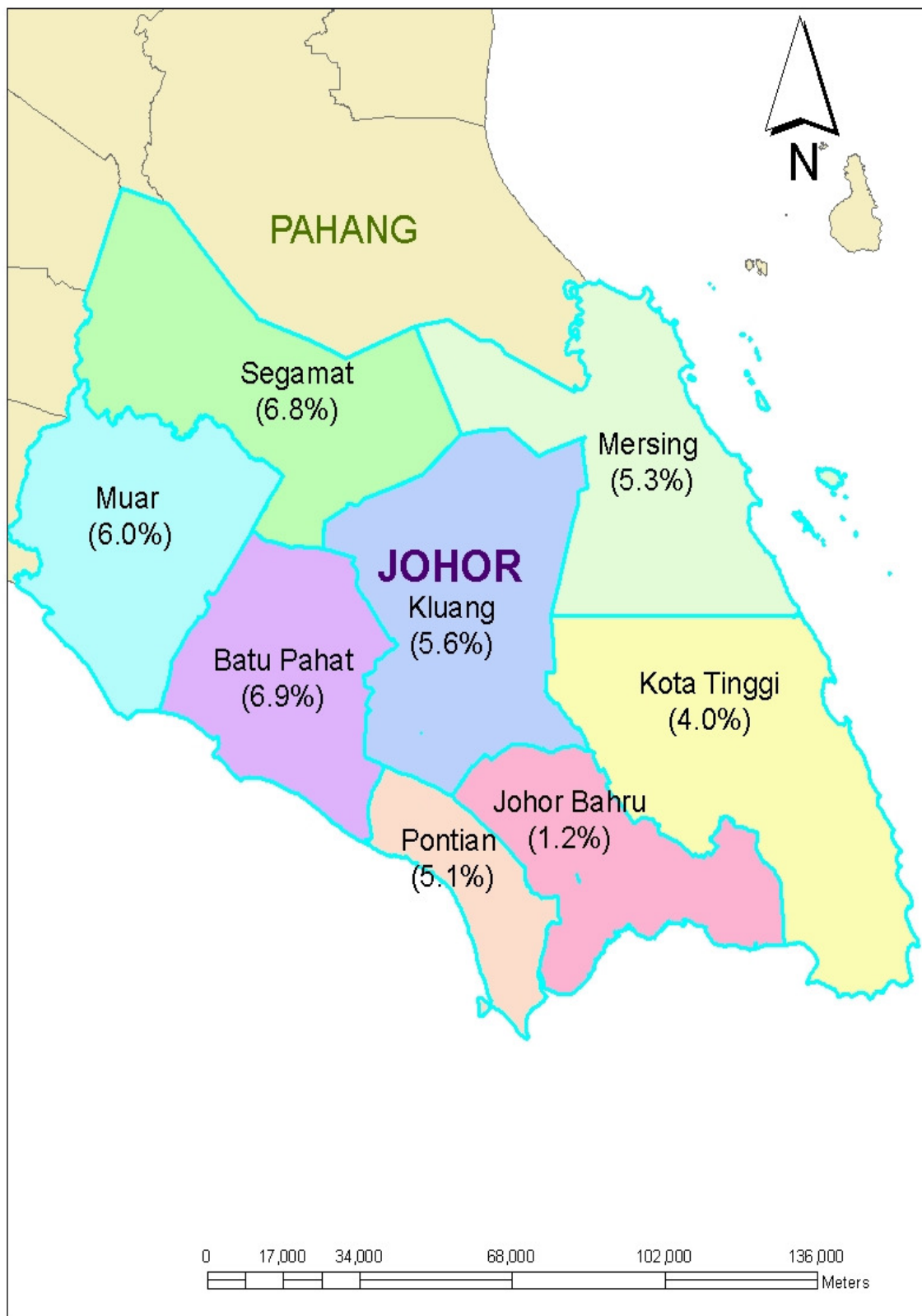
District	SAE (%)	
	Poverty Rate	RSE
Batu Pahat	6.9	9.0
Johor Bahru	1.2	18.1
Kluang	5.6	9.9
Kota Tinggi	4.0	12.8
Mersing	5.3	15.4
Muar	6.0	11.3
Pontian	5.1	12.4
Segamat	6.8	10.2
Johor	3.9	8.5

The application of SAE enables the production of poverty rates by districts. As shown in Table 2, poverty rate ranges from 1.2 per cent to 6.9 per cent. The poverty rate for Johor Bahru (1.2%) deemed to be representing the actual socio-economic scenario of the population. Being the capital state of Johor, Johor Bahru draws population and businesses from surrounding districts within states as well as other states and neighbouring countries. Thus, the poverty rate should be the lowest among the districts within Johor. The high RSE for Johor Bahru can be attributed to the prevalence of poverty at certain pockets of population within the district.

The districts of Batu Pahat and Muar which already belong to the category of metropolitan were expected to record lower poverty rates as depicted for Johor Bahru. However, the higher poverty rates recorded for both districts need to be revisited and analysed further.

From the exercise of SAE, the poverty rates by districts can be portrayed in the form of maps using Geographic Information System (GIS). Generally, the GIS map should be able to provide more information for certain location, provided the GIS data contains the information such as schools, health facilities, basic infrastructures and others. With this information, more detailed analysis can be undertaken at the district level in facilitating the poverty targeting program.

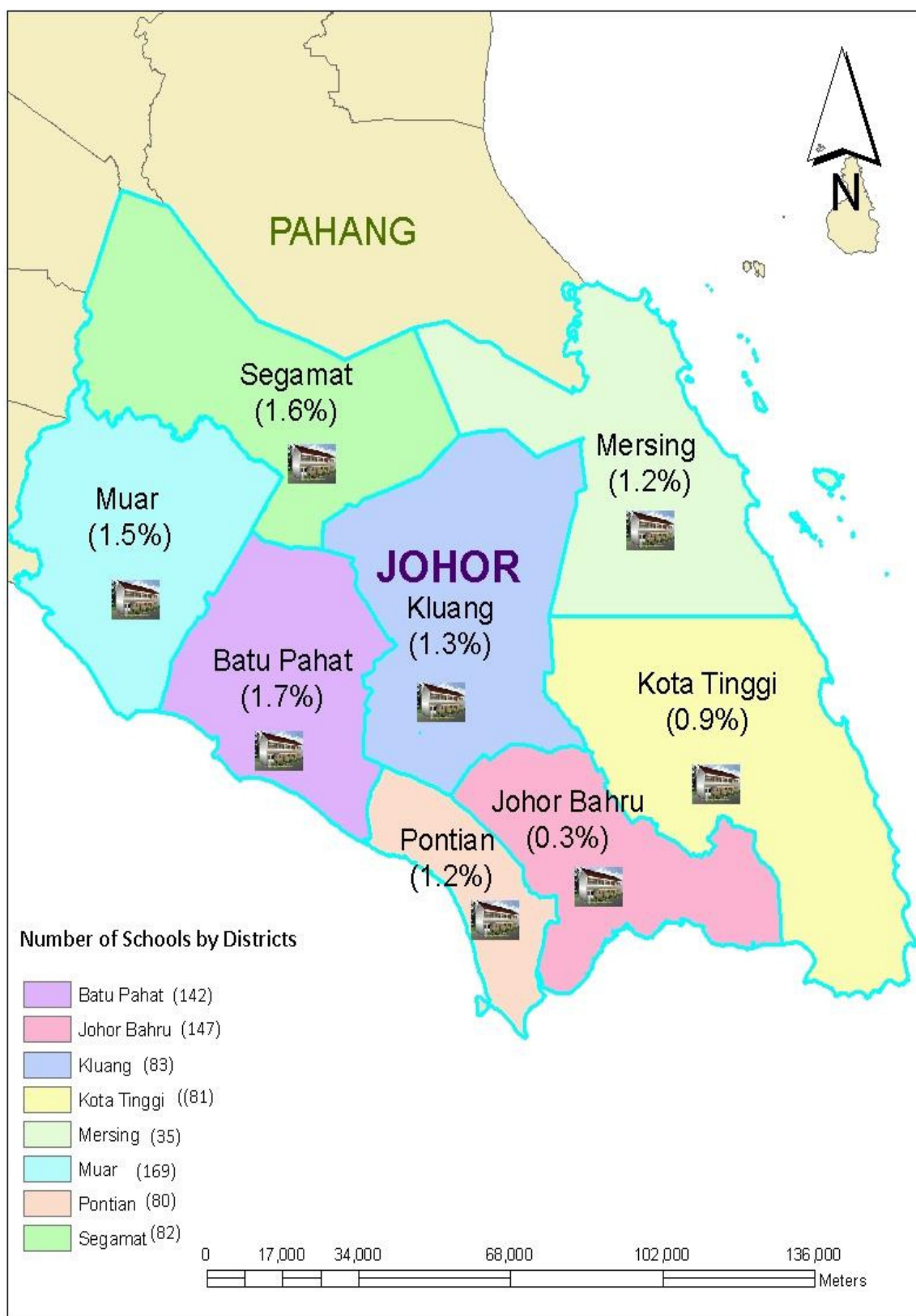
Figure 1: Poverty rate by district, Johor, 2007



The district of Johor Bahru recorded the lowest poverty rate (1.2%), while the rest of the districts in Johor recorded poverty rates of 4 per cent and above. The lowest rate for Johor Bahru district can be attributed to its status as the metropolitan capital city of Johor and its location as the nearest district to Singapore. Hence, it has a better economy due to higher job opportunities and good infrastructure.

On the contrary, the activities in rural areas of Segamat were mainly related to the agricultural sector. Furthermore, The Preliminary Count Report for Urban and Rural Areas in Census 2000 also stated that the percentage of persons who is living in rural area was 46.4 per cent. This probably contributed to higher poverty rates in the district which was 6.8 per cent.

Figure 2: Poverty Gap rate and number of schools by districts, Johor, 2007



Poverty gap is an indicator that measures the percentage of individual living below the poverty line over the population. Lower poverty gap shows less magnitude of people living below the poverty line. In line with the poverty rate, the lowest poverty gap was recorded in the district of Johor Bahru (0.3%) while the highest was in Batu Pahat (1.7%). The calculation of poverty rate and poverty gap was based on the poverty line income of Johor.

Generally, the findings of poverty mapping showed that the rural areas have higher poverty rates. Therefore, the appropriate targeting of eradicating poverty programmes should also taken into consideration the geographical locations of the poor households. The specific location which indicated by the small area statistics could be used as a benchmark for the government in formulating the specific programmes for the poor households. The list of poor households from eKasih database could also be used as reference. The poverty eradication programmes such as 1AZAM was formulated by taking into consideration the skill and interest of the poor households which are being categorized into four areas namely Azam *Khidmat*, Azam *Niaga*, Azam *Tani* and Azam *Kerja*.

Way Forward

The SAE is able to produce the best estimate at the lower area with a small RSE. With the difference of seven years, the estimated result at state level is higher than the official results. However, this case study managed to produce the estimated figures to district level only. Due to the availability of the Census 2010 and the latest HIS 2009, it is timely to produce the latest small area statistics and probably to enhance the estimates to sub-districts level. The poverty statistics including the small area statistics is crucial as the government is targeting to reduce and identify the poor household in order to achieve the high income country by 2020. The effort to look into the poverty scenario in Johor using the poverty mapping technique provides a better understanding about poverty and subsequently identifying the location of the poor households.

The SAE method using the household level unit analysis could be the best estimates compare to the other approach such as direct estimate which assumed that all the small areas have the same rate of poverty rate as the state level. Thus, this rate would be multiply with the district's population to get the number of the poor peoples. The estimates are quite rough as it is not taking into consideration the characteristics of the locations as well as other factor such as socio-economic of that particular district.

Based on the capabilities of this method to produce the small area statistics by district in Johor, the technique would be expanded to other states in Malaysia. The statistics produced for each state and districts would facilitate the government in channeling the resources to the right target group. In Government Transformation Program (GTP), one of the main targets is to eradicate poverty. Thus, with the comprehensive statistics at small area besides facilitating targeted programmes for the poor, it also enhances the public delivery system.

As a leading statistical agency in Malaysia, it is crucial for the department to produce small area statistics specifically in poverty as well as in other socioeconomic fields.

The department has outlined in the Strategic Plan 2010-2014 to enhance the GIS to incorporate more auxiliary variables on the map. The variables such as roads, rivers and other basic infrastructure help users in obtaining comprehensive information and in depth analysis could be undertaken.

Conclusion

Poverty mapping is an extremely useful tool for poverty reduction programmes. This is particularly so, if a specific poor area exhibits a lack of public endowment that stifle economic growth. Providing better facilities and infrastructure would promote economic activities in the area and subsequently improved the economic well being of the poor. This leads to better purchasing power and it will enable the poor to graduate from poverty. For example, Thailand has emphasized targeting poverty program at the village level where block grants and other anti-poverty intervention were targeted to the poorest villages. This approach is likely to be a better use of public funds as compared to the overall programmes.

Poverty maps have the advantage of providing a more revealing picture of poverty and some of its determinants within prescribed areas. Thus, the poverty mapping technique is useful for policy makers to target intervention at domestic level and worldwide as it could also monitor and evaluate the effectiveness of projects and policy interventions geared towards the poor. The uses of small area estimates in determining the poverty statistics especially at the district level could be enhanced to the lower levels such as at sub district or perhaps at the enumerations block.

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