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SPATIAL DISTRIBUTION OF POVERTY AT DIFFERENT SCALES

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Abstract

Poverty mapping is usually developed from some sources of data, such as from census and survey data. In some practical application, the poverty was measured usually by household income or expenditure of daily basic consumption.

Using different scales and zoning on a particular set of spatial data may leads to problems in interpreting the results. In practice, organizations publish statistics and maps at a particular area level. Minot and Baulch (2005a) discussed some consequences of using aggregated level data in poverty mapping, which may affect the validity of the output.

The key point of this paper is to compare spatial distribution of the poverty at two different scale, which is the province and district level. How the spatial distribution of the poverty at province level can be use to infer the distribution at the district level. The geographical weighted regression will be applied, and the poverty data of Vietnam will be used as an illustration.

Key Words: *poverty, mapping, spatial autocorrelation, geographical weighted regression.*

JEL Classification: I32, C21, R12

1. INTRODUCTION

Poverty mapping is a visualization of the distribution of the poverty and provides a rich information across the geographical area. Geographic information of poverty can be extremely valuable for governments, nongovernmental organizations and multilateral institutions that want to strengthen the impact that their spending has on poverty (Demombynes et al. ,2002).

Poverty mapping is usually developed from some sources of data, such as from census and survey data. Data from the census were usually available in aggregated form, but the survey data may come at unit level.

Minot and Baulch (2005a) developed a poverty map from aggregated census data. They claimed that the map precision will be reduced as it was created using aggregated census data instead of household.

The objective of this paper is to compare spatial distribution of the poverty at two different scale, which is the province and district level. How the spatial distribution of the poverty at province level can be use to infer the distribution at the district level. The geographical weighted regression will be applied, and the poverty data of Vietnam will be used as an illustration.

2. BACKGROUND AND MODEL FORMULATION

Scale is an important dimension in analyzing spatial data. Its holds a key information on spatial modeling. Atkinson and Tate (2000) wrote that the scale played an important role in developing a spatial model of a particular characteristics.

Gehlke and Biehl (1934) identified a phenomena when analyzing data at two different. Openshaw and Taylor (1981) introduced a term modifiable areal unit problem (MAUP) to figure out the phenomena. Holt et al. (1996) showed that the MAUP is caused by the failure to incorporate spatial effects into the analysis. Anselin (1988) viewed the phenomena as spatial scale effects.

Minot and Baulch (2005b) indicates the important of the spatial distribution of poverty for policymakers and researchers. There are three reasons, firstly knowledge of the patterns will facilitate the targeting of. Second, it is useful in monitoring progress in addressing poverty and regional disparities. Third, it may provide some insight into the geographic factors associated with poverty.

3. POVERTY MEASUREMENT

Foster et al. (1984) and A. Atkinson (1987) discussed a measurement of poverty and inequality based on a defined poverty line. The index was formulated by looking a relative position of each individual into the poverty line. The poverty can also be measured indirectly by considering several indicators which were a proximity of the poor, such as daily food consumptions, infant mortality, human development index, etc. In this paper we look at poverty measures which is called as the Foster, Greer, Thorbecke – FGT (Foster et al., 1984). Some more discussions regarding the FGT can be found in Jolliffe (2006). The FGT is a class of poverty measures index, which is defined by

$$FGT_\alpha = \frac{1}{n}\sum_{i=1} I(y_i \le z)\left[\frac{z-y_i}{z}\right]^\alpha \text{ ; for } \alpha = 0,1,2 \qquad (1)$$

where y_i is expenditure of the i ’th unit, z is the poverty line, n is number of unit in the sample. The first FGT measure is called by the headcount index, for $\alpha = 0$ and can be written into

$$FGT_0 = \frac{1}{n}\sum_{i=1} I(y_i \le z) = \frac{n_p}{n} \qquad (2)$$

where n_p is number of unit below the poverty line z . The headcount index shows a percentage of the population below the poverty line. The second measure is called the poverty gap index, for α = 1, which indicates the average of proportionate income gap. The third measure of the FGT (α = 2) represents the severity of poverty.

4. GEOGRAPHICALLY WEIGHTED REGRESSION

The geographically weighted regression (GWR) was developed by Fotheringham et al. (Fotheringham, Brundson, & Charlton, 2002). The GWR model represent a local relationship between variables, which can be manipulated and mapped to produce a parameter surface across the geographical region. Lets defined a basic global regression as $y_i = a_0 + \sum_{j=1}^{k} a_j \cdot x_{ij} + \varepsilon_i$.

Fotheringham et al. (2002) defined the GWR as an extension of the global regression model by allowing local parameters to be estimated, using the following model

$$y_i = a_0(l_i) + \sum_{j=1}^{k} a_j(l_i) \cdot x_{ij} + \varepsilon_i \tag{3}$$

where l_i indicates the coordinates of the *i'*th point in space. It is important to mention that $a_k(l_i)$ is a realization of the continuous function $a_k(l)$ at point i.

Fotheringham et al. (2002) noted that the unbiased estimate of the local coefficient is not possible,

but estimate with only a small amount of bias can be provided. They assume that the parameters exhibit some degree of spatial consistency, hence estimating a parameter at a given location *i*, can be done by approximating (3) in the region *i* using global model. The process is started by estimating $a_k(l_i)$ using regression on a subset of the points in the data set that are close to *i*. The process continues to the next location, and a new subset of nearby points is created and used. They also assumed implicitly that observed data around the location i have more of incluence in the estimation of the $a_k(l_i)$ than data located farther from *i*.

Fotheringham et al. (2002) defined the GWR by putting a weight on the observation in accordance with its proximity to location *i*. Hence the weight varies with the location *i*, data from observations close to *i* are weighted more than data from observations farther away. They defined the estimate of $a_k(l_i)$ is $\hat{A}(l_i) = \left(X^T W(l_i) X\right)^{-1} X^T W(li) Y$ where $\hat{A}$ denoted an estimate of *A*, which is a

matrix of parameters of equation (3). The $W(l_i)$ is an *n* by *n* matrix whose off-diagonal elements

are zero, and the diagonal elements are the weight of each of the *n* observed data for regression point i. The matrix *A*, can be written as

$$A(l)=\begin{pmatrix} a_0(l_1) & a_1(l_1) & \cdots & a_k(l_1) \\ a_0(l_2) & a_1(l_2) & \cdots & a_k(l_2) \\ \vdots & \vdots & \ddots & \vdots \\ a_0(l_n) & a_1(l_1) & \cdots & a_k(l_n) \end{pmatrix} \quad \textbf{(4)}$$

Each row of the A matrix represents a geographical location points and contains *k* parameters to be estimated, which can be defined as $\hat{A}(i)=\left(X^T W(i) X\right)^{-1} X^T W(i) Y$, where $W(i)$ is defined as

$$W(i)_{n,n}=\begin{pmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \vdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{pmatrix} \quad \textbf{(5)}$$

The *W(i)* is a weighting matrix of the regression point i to the data points around i. If we define w_{ij} = 1 for all *i* and *j*, then we will get the ordinary least square for the global model. Another scheme could be excluded some data that are further than some distance d from the regression point, that is

$$w_{ij}=\begin{cases} 1 \text{ if } d_{ij} < d \\ 0 \; otherwise \end{cases} \quad \textbf{(6)}$$

Fotheringham et al. (2002) defined two models of weighting scheme, that are Gaussian and bi-square function. The Gaussian scheme is defined as follow,

$$wij=\exp\left(-\frac{1}{2}\left[\frac{d_{ij}}{b}\right]^2\right) \quad \textbf{(7)}$$

and the be-square function is defined by

$$wij=\begin{cases} \left(1-\left[\frac{d_{ij}}{b}\right]^2\right)^2 & \text{if } d_{ij} < b \\ 0 & otherwise \end{cases} \quad \textbf{(8)}$$

Where *b* is a bandwidth.

5. DATA

Poverty data were obtained from The Poverty Mapping Project at CIESIN (The Center for International Earth Science Information Network). The socio-economic data at the Earth Institute at Columbia University is funded by the World Banks Japan Policy and Human Resource Development (PHRD) Fund. This Project was a partnership between CIESIN, the World Bank, and the Earth Institute at Columbia University and was undertaken in 2004-2005.

The data is come with two administrative level, which is province and district level. There are 61 provinces, which are subdivided into 614 districts. The poverty measurement being used is the headcount index -- *FGT(0)*, and some socio-economic indicators. The variables are area (area in km square), denshh (number of households per km square), fgt0 (headcount index – FGT for $\alpha = 0$), pliter (pct of literate person ≥ 15 years old), pelect (pct of household with electricity), pradio (pct of household with radio), ptelev (pct of household with television), pagric (pct of person in agriculture), pdepen (pct of dependence person), pfemal (pct of female), pbelow (pct of person below 15 years old), pupper (pct of person upper 65 years old), pbetwe (pct of person between 15 - 64 years old)

6. RESULT

Descriptive statistics of the indicators are found in Table (2).

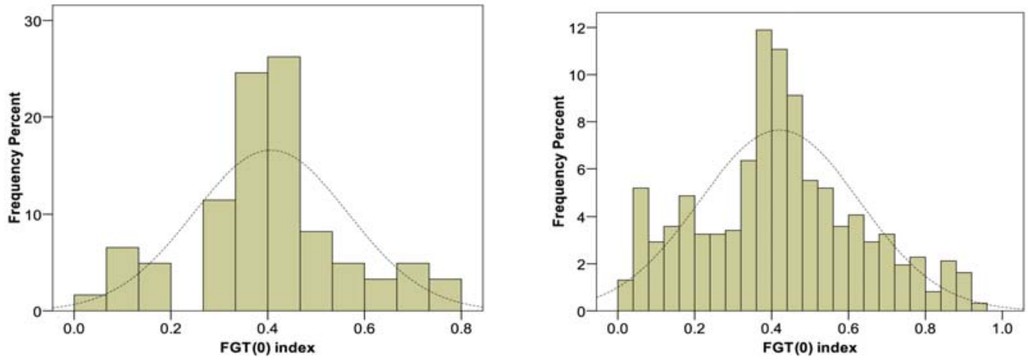
Table 2. Descriptive statistics of the poverty index and indicators for the province and district level

level of data		Minimum	Maximum	Mean	Std. Deviation	Variance
Prov.	FGT(0) index	.05	.80	.41	.16	.03
	Area (km2)	804.00	19,599.00	5,397.26	4,264.34	18,184,601.06
	Pliter	30.20	73.64	58.01	8.22	67.52
	pelect	28.02	99.68	71.83	21.15	447.20
	Pradio	32.19	66.48	44.42	8.06	64.99
	ptelev	23.71	83.86	50.23	12.43	154.48
	pagric	3.07	45.09	34.15	8.84	78.20
	Pdepen	29.13	47.12	39.87	3.64	13.25
	Pfemal	48.92	52.35	50.76	.76	.58
	pbelow	23.90	43.40	34.35	4.13	17.05
	pupper	3.10	8.85	5.51	1.37	1.88
	Pbetwe	56.60	76.10	65.65	4.13	17.05
	Denshh (per km2)	6.06	697.68	102.40	124.83	15,581.73
district	FGT(0) index	.03	.94	.42	.21	.04
	Area (km2)	4.00	5,043.00	534.90	539.69	291,266.65
	Pliter	12.25	79.50	57.23	11.47	131.67
	Pelect	2.78	100.00	69.70	27.51	756.75
	Pradio	17.81	98.15	44.05	11.10	123.21
	Ptelev	1.35	98.15	48.18	19.69	387.86
	Pagric	.13	51.09	34.10	13.09	171.34
	Pdepen	23.87	53.15	40.02	5.05	25.54
	Pfemal	39.33	53.41	50.66	1.12	1.25
	Pbelow	19.14	50.04	34.64	5.64	31.77
	Pupper	.00	10.06	5.39	1.65	2.74
	Pbetwe	49.96	80.86	65.36	5.64	31.77
	Denshh (per km2)	1.34	10,064.25	346.12	1,183.04	1,399,591.17

Sources : computation result.

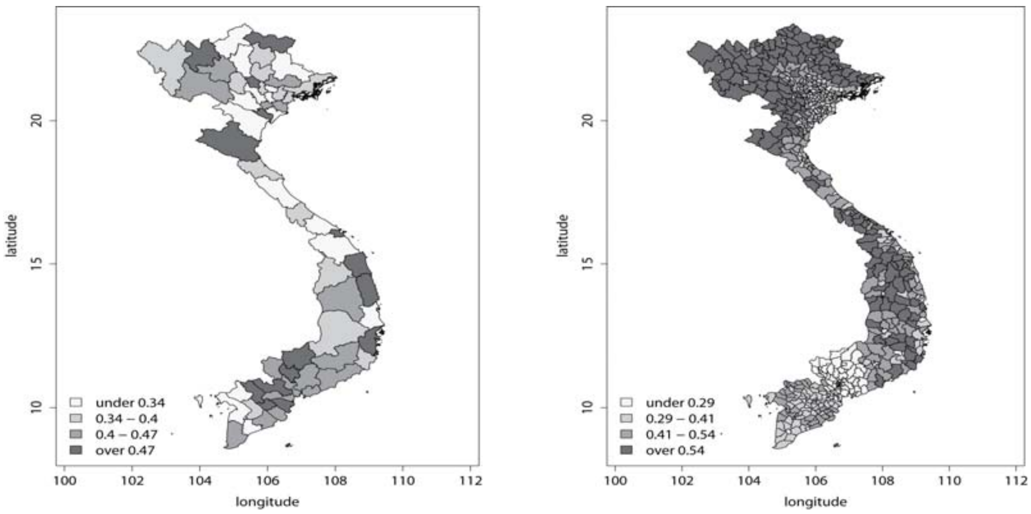
Distribution of FGT(0) index at province level look almost similar with its corresponding district level, as shown in Figure 2. The district level has a larger variations, and the same median with the province level. But from Figure 3, we found a very different distribution of FGT(0) across the geographical locations. At the district level was found a larger FGT(0) at the northern area.

Figure 1. Distribution of the FGT at at the province and district level



(a). Province level (b) District level

Figure 3. Distribution of the FGT at at the province and district level



(a). Province level (b) District level

The GWR models are a local regression model, which were generated at neighbourhood points. Median of the estimated GWR coefficients model either at province or district level are comparable with corresponding global model.

Applying the GWR, we find the following result for the province level :

```
Call:
gwr(formula = fgt0 ~ pliter + pelect + pradio + ptelev + pagric +
   pdepen + pfemal + pupper + denshh, data = vnm1, coords = cbind(vnm1$x,
   vnm1$y), bandwidth = fgt0.bw, hatmatrix = TRUE)
Kernel function: gwr.gauss
Fixed bandwidth: 549.5374
Summary of GWR coefficient estimates:
                Min.    1st Qu.    Median    3rd Qu.      Max.    Global
X.Intercept. -4.745e+00 -3.620e+00  1.394e+00  1.839e+00  3.538e+00    2.4148
pliter       -1.899e-02 -1.790e-02 -1.421e-02 -7.165e-04  8.139e-04   -0.0115
pelect       -2.311e-03 -1.716e-03 -1.554e-03 -1.028e-03  1.729e-03    0.0007
pradio       -2.779e-03 -1.786e-03 -1.509e-03 -2.265e-04  8.820e-04 3.314e-05
ptelev       -7.118e-03 -6.031e-03 -3.613e-03  2.473e-03  3.632e-03   -0.0048
pagric        2.584e-03  2.740e-03  2.930e-03  3.160e-03  4.476e-03    0.0052
pdepen       -9.931e-03  1.279e-03  5.023e-03  2.078e-02  2.462e-02   -0.0057
pfemal       -4.188e-02 -1.727e-02 -1.102e-02  7.624e-02  9.536e-02   -0.0238
pupper       -2.903e-02 -2.476e-02  2.742e-02  4.228e-02  4.591e-02    0.0176
denshh       -3.444e-05  9.592e-05  1.139e-04  3.343e-04  4.676e-04    0.0001
Number of data points: 61
Effective number of parameters: 22.87200
Effective degrees of freedom: 38.12800
Sigma squared (ML): 0.001314570
AICc (GWR p. 61, eq 2.33; p. 96, eq. 4.21): -167.3010
AIC (GWR p. 96, eq. 4.22): -211.8747
Residual sum of squares: 0.08018879
```

And the GWR model for district level :

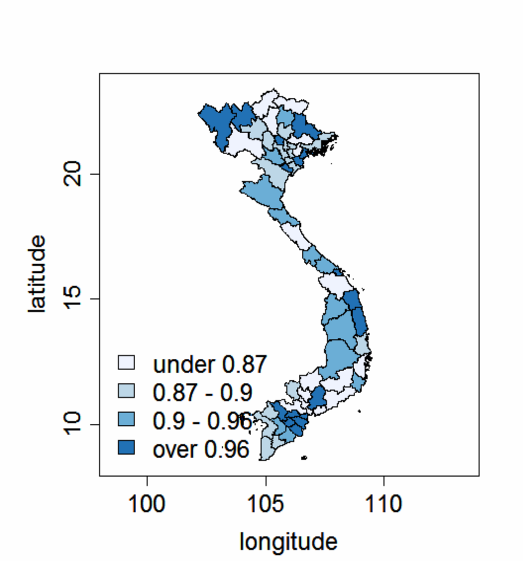
```
Call:
gwr(formula = fgt0 ~ pliter + pelect + pradio + ptelev + pagric +
   pdepen + pfemal + pupper + denshh, data = vnm2, coords = cbind(vnm2$x,
   vnm2$y), bandwidth = 63.4385, hatmatrix = TRUE)
Kernel function: gwr.gauss
Fixed bandwidth: 63.4385
Summary of GWR coefficient estimates:
                Min.    1st Qu.    Median    3rd Qu.      Max.    Global
X.Intercept. -5.371e+00  7.934e-01  1.379e+00  2.007e+00  4.877e+00    1.6032
pliter       -2.206e-02 -9.368e-03 -6.778e-03 -3.738e-03  1.534e-02   -0.0070
pelect       -5.508e-03 -2.091e-03 -1.535e-03 -8.923e-04  2.647e-03    0.0002
```

pradio	-7.784e-03	-1.708e-03	-9.178e-04	-1.503e-04	1.621e-02	0.0002
ptelev	-1.307e-02	-4.289e-03	-3.462e-03	-2.085e-03	4.239e-03	-0.0049
pagric	-4.896e-03	1.155e-03	2.602e-03	3.601e-03	1.067e-02	0.0036
pdepen	-2.717e-02	-3.836e-03	6.784e-04	4.622e-03	3.901e-02	0.0002
pfemal	-5.922e-02	-1.223e-02	-7.032e-03	2.094e-03	8.847e-02	-0.0149
pupper	-5.598e-02	-8.071e-03	7.323e-03	2.229e-02	8.407e-02	0.0089
denshh	-5.667e-04	-3.192e-06	2.887e-06	7.643e-06	1.071e-03	1.061e-05

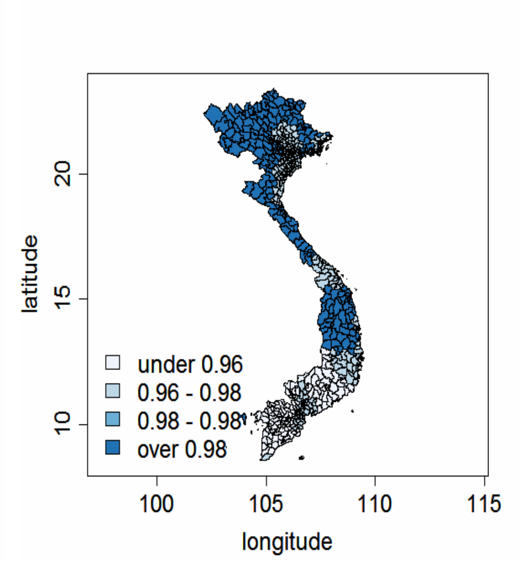
Number of data points: 614
Effective number of parameters: 269.9365
Effective degrees of freedom: 344.0635
Sigma squared (ML): 0.0005393224
AICc (GWR p. 61, eq 2.33; p. 96, eq. 4.21): -2207.847
AIC (GWR p. 96, eq. 4.22): -2662.588
Residual sum of squares: 0.3311439

The GWR model for province and district level can be compared in term their R-square. The GWR model at district level give higher R-squared, especially at the northern area, compare with the GWR model at province level (Figure 4). But it was lower at the southern area. Figure 4 gives information that for the province level, the independent variables gives estimates of the FGT(0) only at a particular area when the R-square was high. But for the district level, the indipendent variables may give a good estimate of FGT(0) at whole northern area, but not at southern area. Figure 3 also indicate that spatial autcorrelation for the district level seems higher than the province level. This condition can be a reason of the result in Figure 4 (b).

Figure 4. Distribution of R-squre for each level by the GWR model.



(a) Province level



(b) District level

7. CONCLUSION

Targeting the poor within the region can be a tough problem and need more detail information to get a better result. The GWR model can be used to help approaching the poverty index of the area, in this case the FGT(0), by observing some variables which were more easy to be measured. Information at the district level can be used better than the province level.

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