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ELUCIDATING THE SELF-FORMATION OF LOW-INCOME SOCIO-ECONOMIC' CHARACTER USING GEOSPATIAL ANALYSIS MODELLING

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Abstract: This study developed an alternative method for the local analysis of relationships between low-income socio-economics' character among the various local modelling approaches, Geographical Weighted Regression (GWR). The complexity originates from the integration of spatially and temporally varying factors underlying the interpretation of socio-economic environmental elements. In addition to spatial autocorrelation and spatial non-stationarity exist widely in Geospatial analysis processes, which are incorporated with Ordinary Least Square (OLS) model. The result found GWR models has achieved better performance than the global OLS model, which the individual data on averages are calculated and explained the locational information and link problematic structure on a map. The techniques are applied and generated the exploratory spatial data analysis, to analyse the spatially varying relationships of low-income socio-economic indicators across low-income settlement point'sdatabase of Bangkok, Thailand. Thus, the self-formation of spatial analysis is characterized and explored scale effect on low-income settlement approaches by the location of socio-economic environmental features. It is possible to offer useful alternatives this novel idea joint application of urban planning and policy decision-making when assessing GWR model.

Keywords:Geographical weighted regression (GWR), Ordinary least square (OLS), Low-income socio-economics' character, Self-spatial formation, Geospatial analysis.

I. INTRODUCTION

Low-income settlement is the one of serious problem, which is often associated with urban development in many developing countries. The impacts of low-income settlement on urbanization and urban form crisis in above previous studies are all caused by human activities, and most of the habitants are lived to be poor (Shrestha, et al., 2008). Thus the information of Bangkok, the capital of Thailand, has grown rapidly over the past decades with socio-economic development parallel. Especially, low-income people are hardship of being poor condition compared to general households, which is residing near low-income settlement area. However, the level of urbanization of Bangkok is lower than the Asian average but it is still continue every year and concerned population is preferred destination for rural-urban migrants, as the country's economic centre such as the place to find jobs and earn income to support their relatives.

The core ideas of study are introduced to offer the spatial data analysis and multivariate statistical method based on high-resolution assessment using an agglomeration technique on the extracted components in term of socio-economic environmental factors of low-income settlement condition in Bangkok. The classification grouped with the specific characteristic type of low-income settlements in study area (see Fig.1). There are offer an impartial basis for a wide range of socio-economic vulnerability indices represent a potentially useful tool for identifying areas of greatest concern in term of the relative level, underlying the accuracy and homogeneity of low-income socio-economics' character to environmental changes across broad spatial scales.

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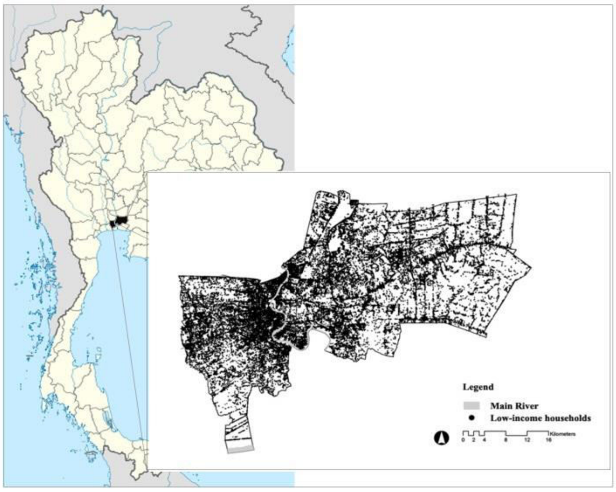

Fig. 1 Bangkok, the low-income settlement point in 2009 using the definition of National Housing Authority (NHA)

To aggregate the significant of spatially low-income characteristic varying relationship between dimensions of spatial non-stationarity data. This study will be examined to attempts the significant advances of low-income socio-economic characteristic from Principle Component Analysis (PCA) result, which is possible to calculate the standard deviation of a set of observations with a weight attached to each observation in spatial analysis using GIS-Geographically Weighted Regression (GWR).

GWR is local spatial statistical technique for exploring the assumption of parameter than observations at greater distance; it is developed on the basis of tradition regression framework, which incorporates local spatial relationship into framework in an intuitive and explicit manner (Fotheringham and Brunsdon, 1999). The innovation with GWR is using a subset of data proximate to the model calibration location in geographical space instead of variable space. The result of GWR is estimating or predicting the response variable of low-income settlements' character, which has been presented as a method to conduct inference on spatially varying relationships in an attempt to extend the original emphasis on prediction on confirmatory analysis (Paez and Wheeler, 2009).

This study focuses on the local varying dynamics of low-income socio-economics' character patterns in response to urbanization and urban form condition in Bangkok using GWR model in addition to OLS model to incorporate the effects of spatial clustering. The objectives are refer to (1) apply socio-economics' character to identify the local variations in low-income settlement patterns as well as their changes; (2) employ GWR to analyse the local varying relationships between urbanization and urban form condition of low-income settlement patterns; and (3) attempt the significant of low-income socio-economic environmental features area on local varying relationship. The results can be found the characteristic of low-income socio-economic' settlement and planed for solving the low-income solution.

II. APPLYING GEOGRAPHICALLY WEIGHTED REGRESSION METHODS

GWR is widely employed in geographical analysis, can be used to examine spatial variation in the relation between outcomes and explanatory variable (Brunsdon et al., 1996). Moreover, the compared GWR with some statistical models, GWR can estimate regression coefficients at any one spatial location and give significant improvement for the response variable than those derived from other model (Zhang et al., 2005). By appropriate application of GWR model, it is possible to determine spatial variations in the relationship between response and explanatory variables and different scale at which the regression model has the best predictive performance (Foody,2004).

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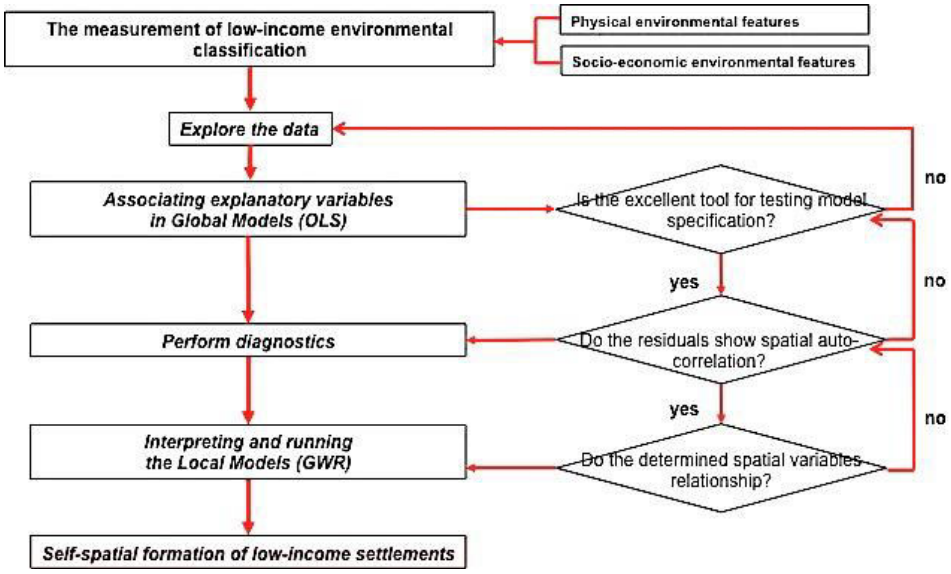

Fig. 2 The analytical process

In contrast, GWR does not have all the great diagnostics to help the figure out whether the explanatory variables are statistically significant, your residuals are normally distributed or ultimately. In addition, GWR will not fix an improperly specified model unless the factors can be sure that the only reason model is failing the result of non-stationarity. Therefore, this study was associating explanatory variables in global model using Ordinary Least Square (OLS), which is the basic regression analysis among the various local modeling approaches. There are associated GWR with OLS when applied to geographical interactions, which can estimate the models in ArcGIS by expanding within ArcToolbox (see Fig.2).

I. OLS method

Ordinary Least Squares (OLS) regression model is phenomenon that is being studied and variable to assume a stationary process. There is computes both the probability and robust probability for each explanatory variable. OLS is global model that is expecting variable relationships to be consistent across the study area. OLS is common social science statistic used to evaluate the relationship between multiple variables. The resulting single regression equation is the representation of complex relationships between variables, which is generated by ArcGIS along with the model area summary such as Coefficient Sign, Probability / Robust Probability (Prob), Adjusted R-Square (R2), Corrected Akaike Information Criteria (AICc), Jarque-Bera P-Value (JBP), Koenker'sStudentizedBreusch-Pagan P-Value (KBP), Variance Inflation Factor (VIF), Global Moran's I P-Value (MI), Joint F-Statistic and Joint Wald Statistic (JFS/JWS) (ArcGIS 10.1).The OLS regression model with one predictor variable is:

$$y = \alpha + \beta X + \varepsilon \qquad (1)$$

Where y is the dependent variable and X is the explanatory variable.α, β are parameters to be estimated. ε is a mean zero random error term with constant (but unknown) variance and normally distributed. Assuming that these conditions are satisfied, the parameters can be estimated using OLS.

The limitation of OLS estimation in spatial process models, the spatial dependence in the various spatial auto-regression models shows many similarities to the more familiar time-wise dependence. Therefore, one would expect the properties of least squares estimation for models with lagged dependent variables and/or serial correlation to translate directly to the spatial case. However, this is not so. The lack of direct analogy is primarily due to the two-dimensional and multidirectional nature of dependence in space (Aselin, 1998).

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By using OLS, this step can perform diagnostics with statistically significant non-stationarity are especially good candidate for GWR analysis. OLS is interpreting the common approach to regression analysis results for more information before moving to GWR.

II. GWR method

In particular, GWR is local estimation of model parameters, which is obtained by weighting all neighboring observations using a distance decay function, assuming that the observations nearby have more influence on the regression point than the observations further away. Like OLS, GWR builds a model to analyze how one dependent variable changes in response to the change in one or more independent variables. However, unlike OLS that generates a set of regression results applied to all the regression points, GWR can calculate a set of local regression results including local parameter estimates, the values of t-test on the local parameter estimates, the local R^2 values, and the local residuals for each regression point (Tu, 2011). Therefore, GWR provides a useful tool to explore the spatially varying relationships between low-income socio-economic characteristic approaches. By increasing application of GWR, this approach is effective in addressing the problems of spatial non-stationarity and spatial auto-correlation in model residuals, which are associated with OLS when applied to geographical interactions (Clement et al., 2009)

Compared to global regression, GWR is only technique specially designed for exploring spatial non-stationarity, defined as when the nature and significance of relationships between variables differs from location to location (Fotheringham et al., 2002). It can be used to examine how regression parameters and model performance vary across a study region. Li, et al., (2010) found the comparison between GWR and OLS methods; it was presented that GWR model can provides a better fit than the traditional OLS model. There are 2 ways in which GWR differs from conventional linear regression; (1) a separate regression is carried out at each location or observation using only the other observations that fall within a user-specified distance or spatial kernel surrounding that location; and (2) the technique includes a statistical methodology that weights the attributes of nearby observations within the kernel more highly compared to the attributes of distant observations.

A technique of GWR likes assessing local influences, allowing for spatial variance in parameters and possibly a more appropriate fit. A detailed description of GWR is given by Fotheringham et al., (2002), which can be calibrated a single regression equation for all observations by global regression as:

$$y = \beta_0 + \sum \beta_k x_{ik} + \varepsilon \qquad (2)$$

Where the y is the estimated value of the dependent variable for observation I, β_0 is the intercept, β_k is the parameter estimate for variable k, x_{ik} is the value of the k^{th} variable for i, and εis error term.

GWR constructs a separate regression equation for each observation and each equation is calibrated using a different weighting of observations contained in data set. GWR model allows local rather than global parameters to be estimated and the above model is:

$$y = \beta_0(u_i,v_i) + \sum \beta_k(u_i,v_i)x_{ik} + \varepsilon_i \qquad (3)$$

Where (u_i,v_i) indicates the coordinates of thei^{th} point (or sample) in space.

The main output from GWR is a set of location-specific parameter estimates, which can be mapped and analyzed to provide information on spatial non-stationarity in relationships. There is calibrated for various applications, and its limitations and opportunities have been discussed widely in the scientific literature. This study provides various on GWR, which are explored spatial variations in the relationship between socio-economic conditions of low-income settlement approaches across urbanization and urban form crisis in Bangkok, Thailand. It is now incorporated in ArcGIS software, written by Bivand and Yu (2011).

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III. EMPIRICAL RESULTS

The relations between low-income socio-economics' character variables are assumed to control erosion, which is commonly modelled using regression. However, it is likely that the influence of some variables may vary with different geographical locations. In such a case, the stationary regression model is unable to show varying spatial relationships, and therefore should be replaced with non-stationary model. While look at the fitted OLS regression using the explanatory variables and also interpret the diagnostics, that it can be accounted and appropriated to use GWR model here.

Each of output will typically begin the regression analysis with OLS and interpreting OLS regression results for more information. Global model, like OLS, created equations that best describe the overall data relationships in a study area. A common approach to regression analysis is to identify the very best OLS model possible before moving to GWR.

Due to the hypothesis, "The spatial locations have been effected to the low-income socio-economic solution", as following the low-income socio-economics' character components of Bangkok 2009;

- *Explanatory Variables (x):*
  1. Contribution of population
  2. Living density
  3. Low-income contribution
  4. Urban taxes
  5. Factories performance
  6. Facility services
  7. Economic activities
- *Dependent Variable (y):* Spatial Location

The result of GWR models show a better performance than OLS models with the same independent variable, as indicated by clear spatial patterns of parameter estimated from GWR models. Nevertheless, its strength in capturing the spatial relationships of given variables at the local level, based on the concept of non-stationarity, is indeed its most important contribution to the quantitative revolution of spatial analysis. Its applications will certainly continue to expand to across the diverse fields of quantitative geography. This approaches provided to context for the result in below.

I. OLS result

Following the PCA results, conventional multiple regression based on ordinary least square (OLS) method is first utilized to examine the simultaneous effects of 7 explanatory variables on low-income socio-economics' character from urbanization and urban form condition of Bangkok. These regression results are summarized in Tables 2 and 3. The ANOVA F test indicates statistical significance for overall model ($p < 0.01$) and the value of the adjusted R-squared (-0.10) suggests a model performance. Moreover, the coefficient of variable is confirmed that the statistically significant means that there maybe non-stationarity in this model. Therefore, GWR can account for appropriate to use here.

Table 2Assess Each Explanatory Variable in Model.

	Coefficient	Std.Error	T-statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	26.277697	11.305229	2.324384	***0.025015***	5.489957	4.786503	***0.000021***	--------
PC1: population proportion	-2.380132	5.864820	-0.405832	0.686927	3.319823	-0.716946	0.477375	1.183590
PC2: living density	5.030061	8.403566	0.598563	0.552679	6.214447	0.809414	0.422838	1.240625
PC3: low-income proportion	-1.970453	6.506788	-0.302830	0.763515	7.298714	-0.269973	0.788505	1.080882
PC4: urban taxes	-2.395173	5.239969	-0.457097	0.649958	2.556172	-0.937016	0.354107	1.008554
PC5: factories performance	-15.977175	21.424157	-0.745755	0.459968	12.270171	-1.302115	0.199173	2.222034
PC6: facilities services	2.859517	3.940005	0.725765	0.472007	2.833097	1.009325	0.318598	1.318862
PC7: economic contribution	0.213848	4.458571	0.047963	0.961973	1.578092	0.135510	0.892857	2.121060

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Table 3 Comparison with the ranges of local R^2 from OLS and GWR

Summary of results	OLS	GWR
R2	***0.048603***	***0.955544***
Adjusted R2	***-0.109963***	***0.912053***
AICc	***530.313360***	***434.11974***
Moran's Index	0.192043	0.157187
Z-score	6.091484	5.692003
P-value	0.000000	0.000000

II. GWR result

To run GWR within the explanatory and dependent variables, the same as OLS model used to estimate in the last section. As a result of Table 2, a global model (OLS) cannot explain the relationships between some sets of variables. Its applications will certainly continue to expand across the socio-economic fields of spatial quantitation using geography analysis. Especially, the AICc score for the GWR (434.11974) was about 20% smaller than AIC from global model (530.313360), which suggest that the local model (GWR) are useful for comparing models with different explanatory variables as long as to the same dependent variable. It is benefit of moving from global model (OLS) to local regression model (GWR).

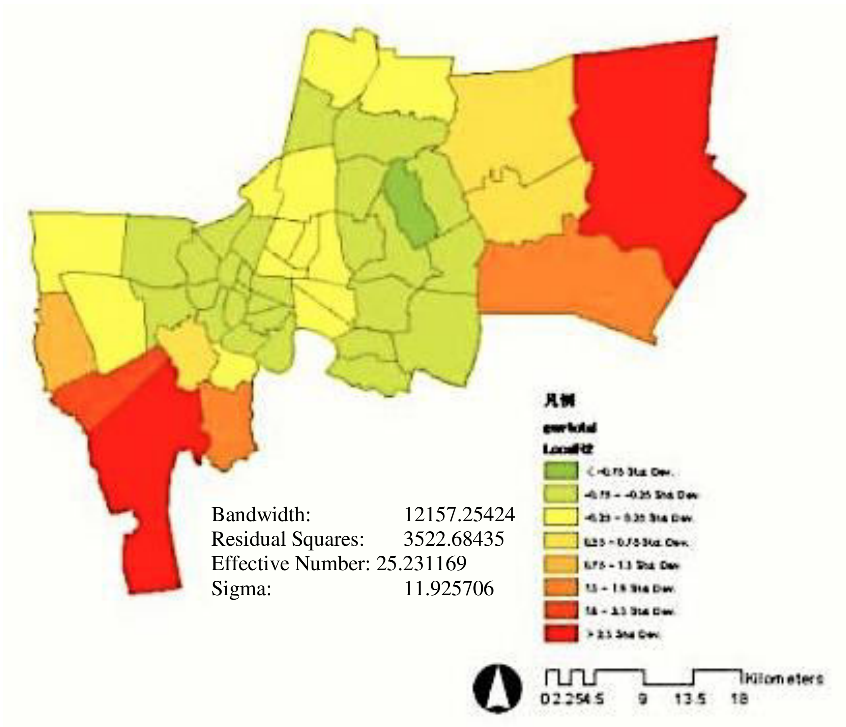

Fig. 3 Results of local R2 on parameters from GWR models

From Local R2, Fig. 3 shown where GWR predicts well, and indicate how well the local regression model fits observed y value (spatial location).

- It was the goodness of fit of local models (GWR) are good with higher value being preferable varying to observed data, which is explains 95% of variance by regression model (GWR > OLS).
- The highest positive spatial effects are identified and forecasted where the variables present stronger tendency to join the existing concentration in that located in the relationship with land use planning heterogeneously effects across local metropolitan areas.

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Based on ranges of local R2, GWR mapping appeared that areas in eastern and western parts of Bangkok have a higher effectiveness of low-income socio-economics' character. This innovative regression approach incorporates a weighting function that give the greatest weight to those locations closet in space to the focal location rather than resorting to arbitrarily defined administrative boundaries (Assunco, 2003).

IV. ELUCIDATION OF LOW-INCOME SOCIO-ECONOMIC STRUCTURE

According to the functional analysis of GWR, generated the self-spatial formation with the transitioning to socio-economic environmental variables taking form by Bangkok database 2009. This structure elucidation is interpreted with low-income settlement location to clarify the socio-economic spatial formation in the highly density area locations of Bangkok (see Fig. 4).

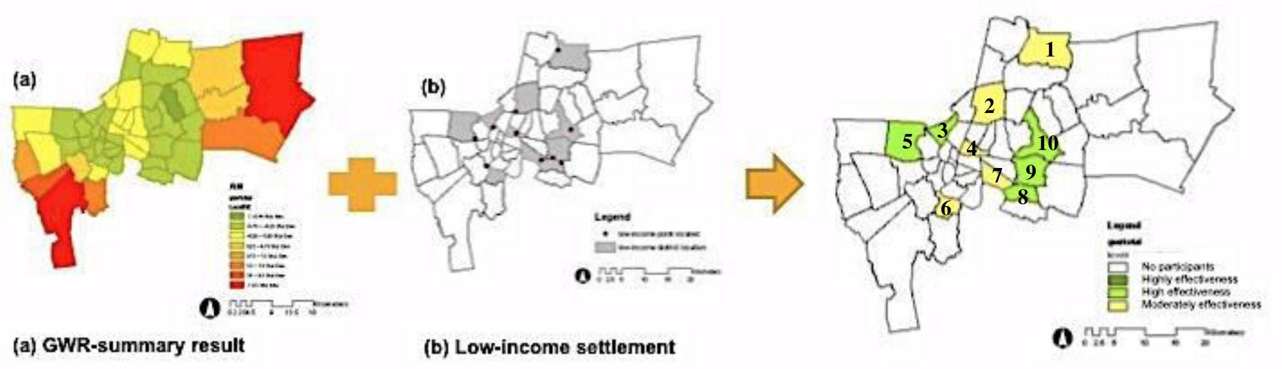

Fig. 4 The structure elucidation process between (a) GWR summary result and (b) low-income settlement location which is generated by highly kernel density analysis (Shummadtayar and Hokao, 2012), (c) the results of self-spatial formation in each district cases.

Actually, the low-income settlements well to do metropolitan areas located in the eastern and western parts of Bangkok had a significantly lower effect than the current location. In particularly, the spatial characteristics of low-income socio-economic features are represented into 2 groups (see Table 4); the high effectiveness solution and moderately effectiveness from socio-economic environment elements such as;

- High economic values, population proportion, density capacity, factories performance, facility services, economic activities, and also the same previously low-income settlement groups
- Within the real condition of urbanized area, easy to find a job, accessing the facilities and services in Bangkok

Table 4The spatial characteristics of low-income socio-economic environmental variables in each case.

Case study number (area)	Classification levels
1	Moderately effectiveness
2	Moderately effectiveness
3	High effectiveness
4	Moderately effectiveness
5	High effectiveness
6	Moderately effectiveness
7	Moderately effectiveness
8	High effectiveness
9	High effectiveness
10	High effectiveness

The combination of multiple indicators of vulnerability into aggregate vulnerability indices must overcome the incommensurability of the units in which the individual indicators are measured. Consequently, this study employed geographically weighted regression (GWR) to characterize the local varying response in the low-income agglomeration to change over space. Among spatial non-stationary and scale-dependent relationships in an attempt to extend the original emphasis on prediction to confirmatory analysis, it is possible to investigate the spatial pattern of the local

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modelling approaches; GWR is the most commonly used estimates to establish some understanding of causes of the pattern. The applications of result will certainly continue to expand across the socio-economic fields of self-formation quantitation using GWR, interpreted with low-income specially area locations to clarify the situation of low-income socio-economic in self-spatial formation.

V. CONCLUSION

This study has certain useful for varying the spatial variations in the relationship between low-income socio-economic features in Bangkok, which is the one of important part of low-income settlement crisis. Under estimated in OLS model to incorporate with GWR model, the statistical inferences that can be drawn from GWR model are relatively limited, which reduces the explanatory power of this model. GWR results also indicate areas to examine the spatial variation within the highly density of low-income settlements for each individual model coefficient.

The findings of this study, GWR also highlightedthe areas formation in its application of a relatively new geospatial analysis of urban planning approach. There have several implications for public policy of low-income settlement socio-economics' character in term of urbanization condition as Bangkok. Moreover, the beneficial of research can be selected and applied to reveal the sensitivity of socio-economic environment results to different scales of analysis. Despite of limitations, the study has important implications for future study and practice, which a result can be helpful in multiple-dimension scale study to generate the effective community interventions using their planning policy and decision-making.

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