

**MODELING HOUSING MARKET DYNAMICS IN THE CITY OF MILWAUKEE: A  
GEOGRAPHICALLY WEIGHTED REGRESSION APPROACH**

**Danlin Yu**

Department of Geography  
University of Wisconsin – Milwaukee  
Milwaukee, Wisconsin, 53201  
Tel: (414) 229-5818  
Fax: (414) 229-3981  
Email: danlinyu@uwm.edu

August, 2004

**Abstract:** This study intends to investigate spatial non-stationarity of the housing market dynamics in the City of Milwaukee. From the 2003 Master Property (MPROP) data file of the City of Milwaukee, a set of owner-occupied single-family houses were randomly selected (representing 99% of confidence within a minus/plus 2% range of accuracy of the total population) to model how house values are related with various house attributes. Remote sensing information, the fraction of soil and impervious surface that represent degraded neighborhood environment conditions, is added to fine-tune the relationship. A geographically weighted regression (GWR) approach is employed to investigate the spatial non-stationarity. The modeling result reveals that significant spatial non-stationarity exists between house values and the determinants. Specifically, the study finds that those house attributes, including floor size, number of bathrooms, air conditioners and fireplaces, add more values to houses in the rich areas, especially on the side of Lake Michigan and suburban areas, than in the relatively poor ones. In addition, older houses in the historical area are more expensive, which differs from other areas. The study concludes that housing market dynamics might be better understood by the combined effects of housing structural and spatial attributes.

**Key Words:** Spatial non-stationarity, housing market, geographically weighted regression, City of Milwaukee

## 1. Introduction

Empirical studies using hedonic house price models have been a common practice of the housing economics and urban study literature since the 1970s. Numerous applications have witnessed that the hedonic house price model is a powerful econometric tool in capturing important determinants of house prices/values regarding both housing structural and locational attributes. However, commentators also noticed that although the theoretical basis of the hedonic house price models was sound and appealing, specification and calibration methodology for the model often received criticism (Mason and Quigley, 1996; Orford, 2000). The traditional hedonic model is usually in a linear form relating the house prices/values to the implicit prices/values of its housing attributes (both structural and locational). The linear model is calibrated by ordinary least squares (OLS) regression in which the regression coefficients represent the implicit prices of various housing attributes. Mis-specification resulting from missing important house value determinants, collinearities among the determinants, and spatial dependence often infest the traditional hedonic house price model.

Moreover, the traditional model is a typical global model. It assumes that there exists a stationary relationship between house prices/values and housing attributes within a metropolitan area. Such postulation has been long challenged and debated among housing economists that a unitary metropolitan housing market might not exist instead it was composed of interrelated submarkets (Maclennan, 1982; Adair et al. 1996; Goodman and Thibodeau, 1998; Whitehead, 1999; Watkins, 2001). As submarkets are relatively homogeneous sub-groups of the metropolitan housing market, relationships vary in different submarkets whilst remain the same within each submarket.

However, a consensus of how metropolitan housing submarkets should be defined and how they could be modeled is far from coming into being (Watkins, 2001). Four common definitions were generally found in the literature (Watkins, 2001), i.e., submarkets delineated by housing structural attributes, geographical locations (space), demander groups, and the joint influence of structural and spatial attributes. Among these delineation methods, empirical studies found that delineate metropolitan house submarkets by demander groups did not yield satisfactory results (Schnare and Struyk, 1976; Palm, 1978; Munro and Lamont; 1985). In addition, it seems quite problematic that housing submarkets can be delineated only by structural attributes or locations alone. In Rosen's (1974) theory of implicit markets, house as a commodity bundle that is composed of both structural and spatial attributes inherently implies that they may not be separable (Orford, 2000). It hence might be more realistic to taking into account both spatial and structural attributes together when investigating urban housing markets.

The practice in the literature in dealing with the joint influence of housing structural and spatial attributes usually takes the way of a nested delineation. That is, the housing market is first grouped by either spatial or structural attributes then further grouped by the other factor around (see Watkins, 2001 for a review). Multilevel (or hierarchical) modeling technique is often employed in such practice (Jones and Bullen, 1994; Goodman and Thibodeau, 1998; Orford, 2000). One particular problem with the application of multilevel modeling technique is that the analysts' *a priori* knowledge and understanding of the local housing market plays significant role in the final model results. That is to say that although the analysts are aware of the non-stationarity of the relationships between the house prices/values and the attributes, it is assumed that the exact pattern of such non-stationarity is known. Hence a discrete set of boundaries is implicitly imposed on the housing market to identify sub-markets. Distinct differentiation might

be possible on housing structural attributes. It will be unrealistic to assume discrete boundaries on the spatial processes in housing market dynamics, as the effects of space are continuous (Fotheringham et al. 2002).

It is hence to this end this paper intends to promote an alternative methodology, the geographically weighted regression (GWR, Fotheringham et al. 2002), in investigating and modeling the urban housing market dynamics. Specifically, the GWR approach does not assume *a priori* particular patterns of the market non-stationarity. In strict terms, the GWR approach does not even assume *a priori* that there exists market non-stationarity. Instead it employs various statistical and/or simulation methods to test whether such non-stationarity exists. It hence might be an ideal tool in both exploring the non-stationarity of the housing market dynamics and identifying the existence of urban housing submarkets.

The rest of the paper is organized as follows. A brief theoretical investigation of the hedonic house price model and urban housing market dynamics is present in section 2. Section 3 discusses the GWR methodology in detail. Section 4 describes the study area, the City of Milwaukee, Wisconsin, and the data from the Master Property (MPROP) data file and a remote sensing image. This is followed by the analytical results and discussions in section 5. Section 6 concludes the paper with summary of the analysis and future research foci.

## 2. Hedonic model and urban housing market dynamics

### 2.1 Hedonic models

Within the theoretical framework provided by Rosen (1974), the hedonic model is based on the hedonic hypothesis that goods are valued for their utility-bearing attributes or characteristics. The model describes a market equilibrium produced by the interaction between demand and supply in the urban housing market. House in the model is treated as an untied commodity bundle, which includes a variety of house structural and spatial attributes. The model establishes a functional relationship between the observed household expenditures (or assessed values by city assessors) on housing and the housing characteristics contained in the bundle of attributes.

Although Basu and Thibodeau (1998) have grouped such housing characteristics into seven groups regarding lot, improvement, neighborhood, accessibility, proximity externalities, land-used and time when data is collected, they can be generalized as two major categories (Can, 1992). The first category includes the housing structural characteristics, such as lot size, improvement, etc. The second is usually referred to as neighborhood characteristics, which includes all externalities associated with the geographic location of the house, such as the accessibility, proximity externalities, environmental amenities, and land-use information etc. Under such generalization, a hedonic model can be expressed as:

$$P(H) = f(S, N) + \varepsilon \quad (1)$$

where  $P(H)$  is a vector containing house prices/values,  $f(S, N)$  is a functional form with the structural ( $S$ ) and neighborhood ( $N$ ) attributes, and  $\varepsilon$  is the residual term.

Many types of hedonic model specification exist (see Basu and Thibodeau, 1998 for a detailed review of different hedonic model specification). The linear form remains attractive to scholars. The practice of a linear equation has the inherent characteristics that the implicit market (or assessed) value of house attributes can be directly represented by their coefficients. The

linear function is estimated by ordinary least squares (OLS) regression approach in the majority of hedonic research.

## *2.2 Housing market dynamics and spatial non-stationarity*

As aforementioned, the above specification and estimation of the hedonic model is based upon the theory of a unitary housing market functioning in instantaneous equilibrium (Maclennan and Tu, 1996; Orford, 2000; Watkin, 2001). The theory assumes a stationary process between house prices/values and attributes, and very likely is flawed in reality as metropolitan housing markets are usually composed of many submarkets. Specifically, a stationary specification ignores the operational processes and structures that can lead to the disequilibrium in the supply and demand of housing in metropolitan area (Orford, 2000). This in turn will lead to biased/misleading parameter estimates of the hedonic model.

Furthermore, many empirical studies argue that local housing markets can be characterized by functional disequilibrium and segmentation (Straszheim, 1975; Knox, 1995; Case and Mayer, 1996; Goodman and Thibodeau, 1998), as the supply of the housing bundle is typically inelastic. On the other hand, demand for house bundles might be inelastic as well. For many consumers, some of the housing attributes, such as building areas, environmental amenities, neighborhoods etc., might not be substitutable. Schnare and Struyk (1976) argue that housing market segmentation occurs when households' demand for a particular structural or neighborhood characteristic is shared by a relatively large number of households. A direct consequence of market segmentation is a non-stationary housing market.

As the housing bundle is a mix of structural and spatial attributes, it is natural to assume that two types of non-stationary markets, i.e., structural and spatial non-stationary markets, might arise. However, within a metropolitan/urban area, it is also observed that housing structural attributes might not present great variation within the vicinity of relatively small spatial units (Goodman, 1978, 1981; Kim, 2003). It hence might be reasonable to assume that structural non-stationarity could be incorporated in spatial non-stationarity of the housing markets. That is, different housing attributes might have different implicit market prices over geographical areas, whilst structural differentiation can be relatively ignorable within the vicinity of similar geographical areas. Under such speculation, structural and spatial non-stationarity could be consistent. Hence housing market segmentation could be examined through the spatial non-stationary process within the urban/metropolitan area. More importantly, as examining the spatial non-stationarity of housing market does not require distinct delineation of specific segment boundaries, the procedure might be more realistic in understanding the housing market dynamics.

## **3. Methodology of geographically weighted regression**

The geographically weighted regression (GWR) technique is a newly developed statistical methodology specifically in dealing with spatial non-stationarity among regressed relationships. It has recently received intensive attention among scholars (Brunsdon et al. 1996, 1999; Fotheringham et al. 1997, 1998, 1999, 2002; Leung et al. 2000a, 2000b; Huang and Leung 2002, Paez et al. 2002a, 2002b; Yu and Wu, 2004, to name but a few).

In short, GWR develops the idea of Casetti's (1972, 1992) expansion regression method is spatial term. In particular, GWR allows regression coefficients to vary across space in terms of

Tobler's (1970) first law of geography. Within the framework of GWR, the traditional hedonic model expressed in equation (1) can be re-written as:

$$P_i(H) = f_i(S, N) + \varepsilon_i \quad (2)$$

where the subscript  $i$  represents specific geographical locations, and other symbols are defined as in equation (1). (2) indicates that potentially, in different locations, the hedonic equation can take different forms. In a linear specification, equation (2) can be simplified as:

$$P_i(H) = \beta_{i0} + \beta_{iS}S_i + \beta_{iN}N + \varepsilon_i \quad (3)$$

where  $\beta_{i0}$  is the intercept term,  $\beta_{iS}$  and  $\beta_{iN}$  are spatially varying coefficients of structural and neighborhood attributes, respectively.

Calibration of the GWR model follows a local weighted least squares approach. Different from ordinary weighted least squares, when calibrating coefficients on location  $i$ , GWR assigns weights through a weighting scheme to data at locations according to their spatial proximity to location  $i$ . These weights act to ensure that near locations impose more influence on the calibration than locations farther away.

The weights are usually obtained through a spatial kernel function. Two types of spatial kernels are often used, i.e., fixed and adaptive kernels. In a fixed kernel function, an optimum spatial kernel (bandwidth) will be obtained and applied over the study area. This approach is usually less computationally intensive. However, as pointed out by Paez et al. (2002a, 2002b) and Fotheringham et al. (2002), fixed kernel approach can produce large local estimation variance in areas where data are sparse, and may mask subtle local variations in areas where data are dense. On the other hand, the adaptive kernel function seeks a certain number of nearest neighbors to adapt the spatial kernel to ensure a constant size of local samples. This kernel might present more reasonable means in representing the degree of spatial non-stationarity in the study area. In this study, the adaptive kernel function is employed.

To obtain an optimum size of nearest neighbors for the adaptive kernel, a common approach is to minimize the Akaike Information Criterion (AIC) of the GWR model (Fotheringham et al. 2002). The AIC of a GWR model is defined following the works of Hurvich et al. (1998):

$$AIC = 2n \ln(\hat{\sigma}) + n \ln(2\pi) + n \left( \frac{n + tr(\mathbf{S})}{n - 2 - tr(\mathbf{S})} \right) \quad (4)$$

where  $n$  is the total number of observations,  $\hat{\sigma}$  is the maximum likelihood estimated standard deviation of the error term, and  $tr(\mathbf{S})$  is the trace of the hat matrix  $\mathbf{S}$  of the GWR, which is defined as:

$$\hat{\mathbf{y}} = \mathbf{S}\mathbf{y} \quad (5)$$

where  $\mathbf{y}$  and  $\hat{\mathbf{y}}$  are the vector of the dependent variable and the GWR estimated values. The AIC has the general appealing that it could be used to assess whether GWR provides a better fit than a global model taking into account the different degrees of freedom in the two models.

When applying GWR techniques to investigate spatial non-stationarity, it is important to test whether such non-stationarity exists. An  $F$  test (the  $F3$  test in Leung et al. 2000a) based on the sample variance of the estimated model coefficients (Brunsdon et al. 1996; Leung et al. 2000a) is employed to address this concern. Furthermore, although the GWR technique seems to be appealing in addressing spatial non-stationarity and usually will provide better model fit for certain data (Fotheringham et al. 2002), the modeling strategy and calibration procedure are apparently more complex than a global OLS model. It is hence natural to ask whether the increase in modeling complexity can be significantly traded off with the gain in the GWR model.

This concern is addressed via an ANOVA test (Brunsdon et al. 1999; Fortheringham et al. 2002). Those tests are implemented either in the newest GWR software package, GWR 3.0, or in the statistical language environment R (R Development Core Team, 2004). Detailed technique discussions are covered in the listed literature and will not be repeated here.

#### 4. Study area and Data

This study is based on data from the City of Milwaukee, Wisconsin, which is located on the western shore of Lake Michigan (Figure 1). The City grew rapidly during the early 20th century, and formed its current geography in late 1950s. After the current highway network has been completed in the late 1960s and early 1970s, property development in the City stepped into a relatively stable period.

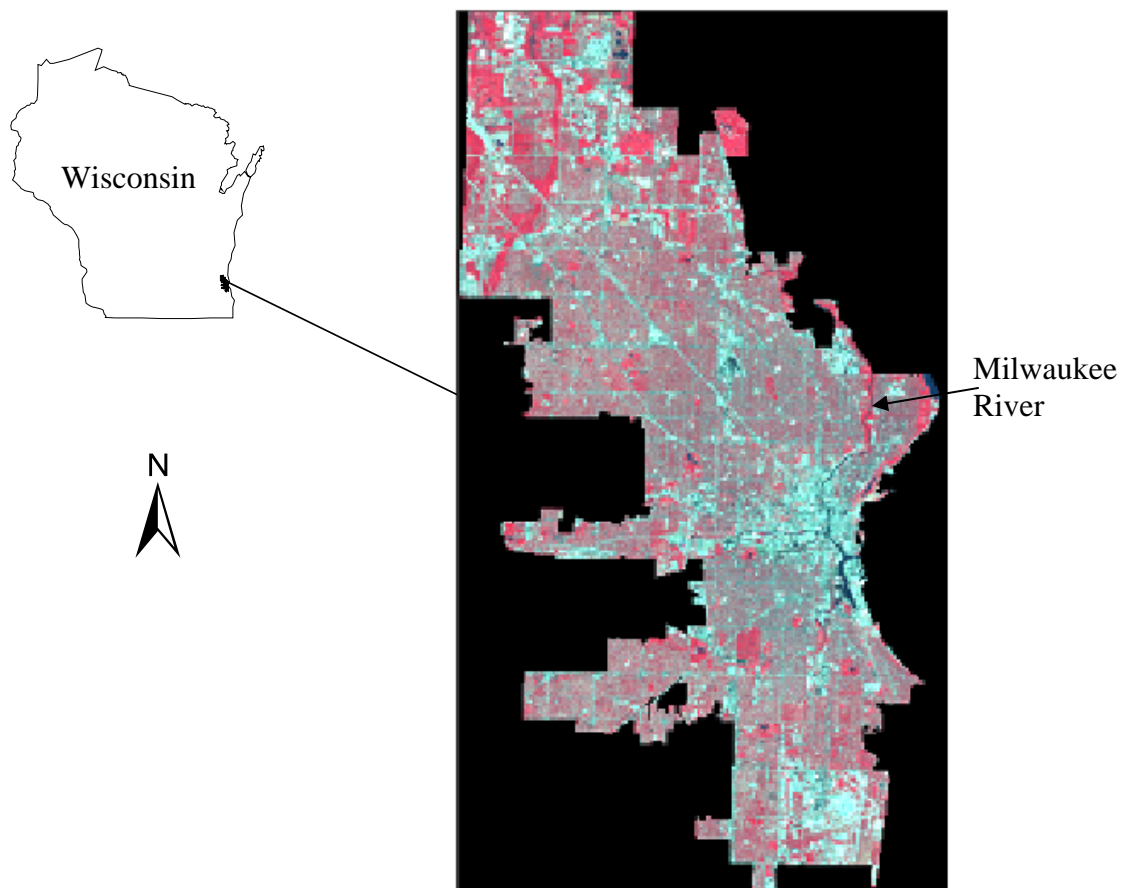


Figure 1. Location of the City of Milwaukee

Two types of data are elected for analysis in this study. The first type is housing structural attribute data that can be extracted from the 2003 Master Property (MPROP) data file of the City of Milwaukee. The MPROP data file has around 160,000 entries of all real properties within the city boundary. Each entry contains more than 80 various attributes including house's location, assessed value, and housing structural characteristics. For the focus of this study, i.e. owner-occupied single-family houses, 68,906 records fall within.

Although it is very attractive to utilize all 68,906 records in building the GWR model, the computation cost is too prohibitive. Hence a random sampling scheme is employed. The sample size is calculated based on 99% of confidence within a minus/plus 2% range of accuracy of the total records. In this study, the final sample size turns out to be 3437 records. A subset operation in the ArcGIS®'s Geostatistical Analyst extension creates the final set of data for analysis.

In addition, from the MPROP data file, it is noticed that only assessed housing values, instead of sale prices, is recorded. Nonetheless, according to the Wisconsin law, the assessed value and the market value of a house cannot vary by more than 10%. It hence might be reasonable to approximate the current house market value by the assessed values.

Except for the assessed house value, five housing structural attributes are identified and retrieved from the MPROP data file as well. In particular, two dummy variables, AirCd and FirePlc, indicating whether central air-conditioners and fireplaces are present or not, and three continuous variables including floor size (FISize), number of bathrooms (NofBath), and house age (HsAge), were chosen to construct the hedonic model in this study. Intuitively, AirCd, FirePlc, FISize, NofBath are hypothesized to be positively associated with the house value, whereas HsAge is hypothesized to be negatively associated.

Table 1 Descriptive statistics for the housing data

Population (68906 records)				
	Mean	Std. Deviation	Minimum	Maximum
House Price	106442.34	55227.78	11000	1249100
Floor Size	1260.54	428.28	413	9154
House Age	60.17	20.52	1	168
Fireplace	0.19	0.45	0	8
Air Conditioner	0.53	0.5	0	1
Number of Bathrooms	1.32	0.46	1	7.5
Soil&Imp. Surface	0.61	0.12	0	1
Sample (3437 records)				
	Mean	Std. Deviation	Minimum	Maximum
House Price	106017.4	57492.04	11000	924000
Floor Size	1260.12	432.38	476	6058
House Age	60.94	20.72	1	156
Fireplace	0.18	0.43	0	4
Air Conditioner	0.52	0.5	0	1
Number of Bathrooms	1.31	0.46	1	6
Soil&Imp. Surface	0.61	0.12	0	0.97

The second type of data is generated from a Landsat ETM+ image (see Figure 1) acquired on July 9, 2001, representing neighborhood environmental conditions. This image was downloaded from the WisconsinView project website (<http://www.wisconsinview.com>) (WisconsinView, 2004). Three environmental characteristics, the fractions of vegetation, impervious surface, and soil for each pixel, are generated using the normalized spectral mixture

analysis method (Wu, 2004). In the preliminary data analysis, it is found that all three remote sensing generated environmental characteristics project significant impact on house values. However, the combined effect of soil and impervious surface (SoilImp), which generally represents deteriorated neighborhood environmental conditions, yields best model performance and is elected in the final model. It is termed neighborhood environmental deterioration index in this study, and is also hypothesized to be negatively associated with the house value. Table 1 reports the summarization of both the population and sample records' descriptive statistics.

## 5. Results and Discussion

### 5.1 Results of the Global model

Using the data and the linear form of equation (2), an OLS regression is carried out and results are reported in Table 2. The model performs fairly well, and two impressions can be taken away from the table.

Table 2 Global OLS regression results for the hedonic model in City of Milwaukee

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	18944.05	4112.79	4.61	4.25e-06
Floor Size	78.88	2.00	39.42	<2e-16
House Age	-508.56	33.45	-15.20	<2e-16
Fireplace	14688.13	1609.53	9.13	<2e-16
Air Conditioner	13412.99	1296.51	10.35	<2e-16
Number of Bathrooms	19697.65	1725.64	11.42	<2e-16
Soil&Imp. Surface	-27926.77	5179.42	-5.39	7.44e-08

Residual standard error: 35230 on 3430 degrees of freedom  
Multiple R-Squared: 0.6252, Adjusted R-squared: 0.6246  
F-statistic: 953.7 on 6 and 3430 DF, p-value: < 2.2e-16  
Akaike Information Criterion: 81731.63

First, the  $F$  test indicates that the model is statistically significant. Moreover, around 62.5% of the variation in the house values is explained by the model according to the adjusted  $R^2$ . This result indicates that the assessed house values in the City of Milwaukee can be modeled by the elected housing structural attributes and the neighborhood environment conditions.

Second, the hypothesized relationships between the structural and neighborhood attributes and the house values are supported by the data. Indeed, all six determinants are statistically significant according to their t-values (Table 2). In particular, as hypothesized, floor size (FlSize), air conditioner (AirCd), fireplace (FirePlc), and number of bathrooms (NofBath) are positively associated with house values, whereas house age (HsAge) and the environmental deterioration index (SoilImp) are negatively related with house values. Since the global model is specified in a linear form, the corresponding coefficients of the individual determinants represent their implicit market prices. For instance, from the global model, in the City of Milwaukee, adding one bathroom will add around \$20000 to the assessed house value, while one year older will cause the house to devalue for around \$500, *ceteris paribus*.

## 5.2 GWR results

The results from the global model reveal important relationship between house values and housing attributes in the City of Milwaukee. However, the relationship is built upon the theory of a stationary housing market, which is likely untenable. In this section, a GWR model is constructed to test and explore such non-stationarity.

The same set of data is used in the GWR model. The model is run through the GWR 3.0 software package (Fotheringham et al., 2002). Tests of non-stationarity based on the variance of the coefficients are conducted in the R statistical language environment. In short, an iterative golden section search of the AIC function (equation 4) reveals that 176 nearest neighbors yield the optimal AIC score. The ANOVA test for GWR against the global OLS model is presented in Table 3, and the non-stationarity tests are reported in Table 4. The varying coefficients and the local  $R^2$  surfaces are produced using ArcGIS®'s spatial analyst. The inverse distance weighted (IDW) method with 12 nearest neighbors and 300-meter cell size is used to create the surfaces. The coefficient surfaces are presented in Figure 2, and local  $R^2$  surface is in Figure 3.

Table 3 ANOVA test of GWR against OLS model

Source	ANOVA Test			
	SS	DF	MS	F
OLS Residuals	4257667878068.3	7.00		
GWR Improvement	3544862425088.0	327.83	10813043388.63	
GWR Residuals	712805558309.1	3102.17	229776586.89	47.06
GWR Akaike Information Criterion: 76317.39 (OLS: 81731.63)				

SS = sum of squares; DF = degree of freedoms; MS = residual mean square

Table 4 Leung et al. (2000a)'s test for non-stationarity

	F statistic	Numerator DF	Denominator DF*	Pr (> F)
Floor Size	2.51	325.76	1001.69	0.00
House Age	1.40	192.81	1001.69	0.00
Fireplace	1.46	80.62	1001.69	0.01
Air Conditioner	1.23	429.17	1001.69	0.00
Number of Bathrooms	2.49	262.39	1001.69	0.00
Soil&Imp. Surface	1.42	375.71	1001.69	0.00

\*: The computation intensity for 3437 samples is too prohibitive. This test is based on another sampling scheme, which reduced the sample size from 3437 to 1059 (Brunsdon, 2004).

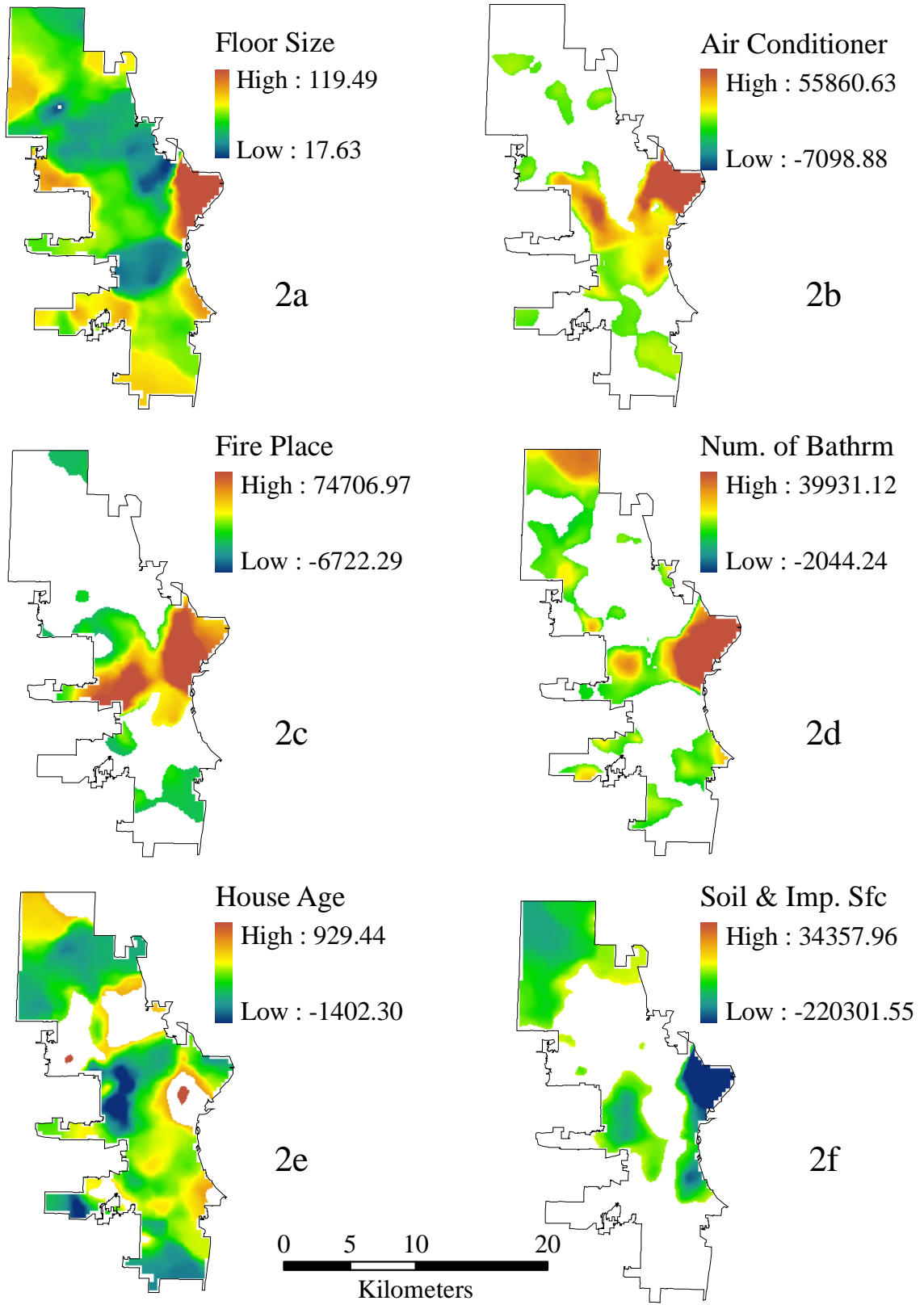


Figure 2 Spatially varying coefficients: 2a. floor size; 2b. air conditioner; 2c. fireplace; 2d. number of bathrooms; 2e. house age; 2f. soil and impervious surface.

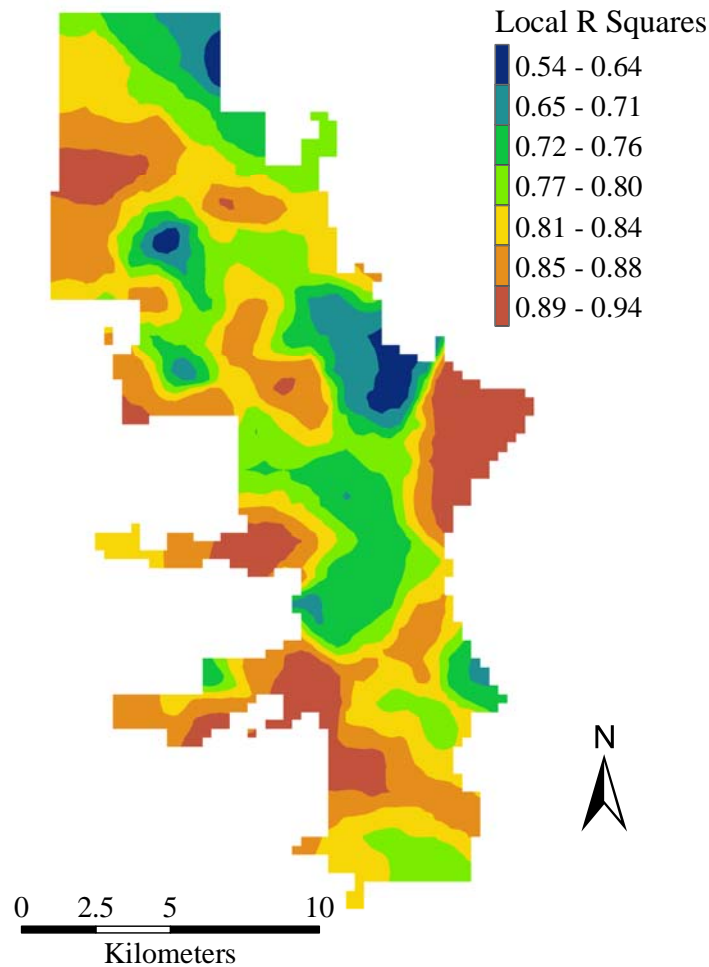


Figure 3. Spatially Varying Local  $R^2$

The ANOVA test (Table 3) indicates that the GWR model has significant improvement over the global OLS model. In addition, the AIC of the GWR model (76317.39) is far less than the one of the global OLS model (81731.63). This indicates that even taking into account the added complexity of the GWR model; it still performs better than the OLS model. Results from Table 4 justify the hypothesis that significant non-stationary relationships between the house value and each of the six structural and neighborhood attributes exist in the City of Milwaukee.

The spatial pattern of such non-stationarity merits further attention. Maps in Figure 2 show the significant surface of each individual attribute's coefficients. The significance of the local coefficients is determined by the local pseudo t-value<sup>1</sup>, which is produced automatically by the software. From the maps, three interesting observations emerge.

<sup>1</sup> Worth noting here is that the local pseudo t-value should not be taken with the same confidence as in a global OLS model. This is because the calculation of the local pseudo t uses neighboring spatial units repetitively. However, the values still suffice to serve the purpose in this study for showing the spatial patterns of the housing market non-stationarity.

First, except for floor size, the established relationship between house values and other structural and neighborhood attributes are not necessarily significant everywhere in the City. That is to say, unlike the global OLS model, within a local modeling environment, some of the elected housing structural and neighborhood attributes do not project significant influence on house values in specific areas. In particular, the maps reveal that in the immediate west side of the Milwaukee River, where most of the City's African-American population concentrates (Yu and Wu, 2004), only floor size and house age are the significant determinants for house values. However, for all attributes, on the other side (east) of the Milwaukee River, the significant relationship between all the attributes and the house values holds. Furthermore, from the local  $R^2$  surface (Figure 3), it is found that the explanatory power differs in these two specific areas. The local explaining powers are among the lowest on the west side of the Milwaukee River, while on the other side, they are among the highest, though interpretation of the local  $R^2$  should not be given the same confidence as in a global model. This result might present a submarket structure based on racial segregation in the City of Milwaukee at the opposite sides of the Milwaukee River. Specifically, for areas at the east side of the River, the elected structural and neighborhood attributes explain the hedonic house values well; whilst on the west side, there might be other determinants than the ones elected in this study influencing house values.

Second, the varying magnitude of the coefficients reveals interesting patterns. The pattern is most salient on the east side of the Milwaukee River, where it is near Lake Michigan. In particular, for all the six elected structural and neighborhood attributes, the closer the houses are to the Lake, the house values are more sensitive to these attributes (Figure 2). That is to say, same amount of change in these attributes (*ceteris paribus*) will bring larger amount of change in house values for houses locate near the Lake than those farther away. This result might suggest an evidence of lake effect in housing market in the City of Milwaukee. Hence, a submarket structure based on the distance to Lake Michigan on the east side of Milwaukee River might be present in the City.

Third, an interesting observation on the relationship between house age and house value emerges in two particular spots, i.e., the northwestern and central eastern part of the City. In these two spots, though they do not cover large area, house age projects significantly positive influence on house values. A closer inspection reveals that these two spots are in areas where the original migrants built their houses. The one on the central eastern part of the City, for instance, is now where the Miller Brewer locates. These facts might imply that older houses are more valuable in these spots because of the added historical values.

## 6. Conclusions

Hedonic house price/value model has been a powerful tool in understanding housing market dynamics in urban housing economics. As most of the studies reveal that the theory of a stationary housing market is likely untenable, this study takes a non-stationary approach. Hypothesizing that the structural non-stationarity might be incorporated in the spatial non-stationarity, the article develops a geographically weighted hedonic house value model utilizing data from the City of Milwaukee, Wisconsin, to investigate such non-stationarity. Statistical tests reveal that significant spatial non-stationarity exists between house values and all the elected housing structural and neighborhood attributes. The spatial non-stationarity is further mapped through GIS and reveals interesting patterns. Specifically, three key conclusions can be drawn based on this study.

First, housing market in the City of Milwaukee might contain many types of submarkets based on locations, housing structural attributes and racial factors. That is to say, delineation and recognition of housing submarkets in the City of Milwaukee need to take into account more than just housing structural or spatial attributes. Instead, the housing markets dynamics in the City are a combined result of all these influential factors.

Second, in the City of Milwaukee, values of houses in the relatively rich areas (such as those near Lake Michigan) are more sensitive to the elected housing attributes than the ones in the relatively poor areas. Moreover, although the elected attributes in this article can account for most of the variations in house values in the relatively rich areas, more determinants might be necessary in understanding housing submarket dynamics in the relatively poor areas.

Third, the spatial modeling technique employed in this article also reveals that historical attributes can add to house values. Whilst in the global model, such subtle effect is masked by the averaging process of the significant spatial non-stationarity. This might suggest that in studying urban housing market dynamics, local modeling technique is more robust than the global ones.

Although the results from this study seem appealing in addressing the non-stationarity in urban housing market, there are still concerns need to be further addressed in future studies. For instance, the model employed in this study relies on housing structural and a remote sensing generated neighborhood attributes, other neighborhood attributes, such as household median income, crime rate, school performance etc. are not included. The GWR result indeed reveals that there might be a possibility that important determinants are missing, especially regarding the house values in the relatively poor areas in the City. Hence the future study will try to identify more determinants than the ones used in this study for better understanding of the urban housing market dynamics.

## **Acknowledgements**

The author would like to thank Professor Yehua Dennis Wei, Changshan Wu, Chris Brunsdon and Stewart Fotheringham for their insightful comments. Any errors and flaws, however, remain those of the author's.

## Reference

- Adair AS, Berry JN and McGreal WS 1996 Hedonic modelling, housing submarkets and residential valuation. *Journal of Property Research* 13: 67-83
- Basu S and Thibodeau TG 1998 Analysis of spatial autocorrelation in house prices. *Journal of Real Estate Finance and Economics* 17: 61-85
- Brunsdon C 2004 Personal communication. Santa Barbara, CA
- Brunsdon C, Fotheringham AS and Charlton ME 1999 Some notes on parametric significance tests for geographically weighted regression. *Journal of Regional Science* 39: 497-524
- Brunsdon CF, Fotheringham AS and Charlton ME 1996 Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical Analysis* 28: 281-298
- Can A 1992 Specification and estimation of hedonic house price models. *Regional Sciences and Urban Economics* 22: 453-474
- Case KE and Mayer CJ 1996 Housing price dynamics within a metropolitan area. *Regional Science and Urban Economics* 26: 387-407
- Cassetti E 1972 Generating models by the expansion method: applications to geographical research. *Geographical Analysis* 4: 81-91
- Cassetti E 1992 The dual expansion method: an application for evaluating the effect of population growth on development. In Cassetti E and Jones JP (eds) *Applications of the Expansion Method* 10-41. London: Routledge
- Fotheringham AS, and Brunsdon C 1999 Local forms of spatial analysis. *Geographical Analysis* 31: 340-358
- Fotheringham AS, Brunsdon C and Charlton ME 1997 Two techniques for exploring non-stationarity in geographical data. *Geographical Systems* 4: 59-82
- Fotheringham AS, Brunsdon C and Charlton ME 1998 Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. *Environment and Planning A* 30: 1905-1927
- Fotheringham AS, Brunsdon C and Charlton ME 2002 *Geographically Weighted Regression: the Analysis of Spatially Varying Relationships*. West Sussex: John Wiley & Sons Ltd
- Goodman A 1978 Hedonic prices, price indices and housing markets. *Journal of Urban Economics* 5: 471-484
- Goodman A 1981 Housing submarkets within urban areas: definitions and evidence. *Journal of Regional Science* 21: 175-185
- Goodman AC and Thibodeau TG 1998 Housing market segmentation. *Journal of Housing Economics* 7: 121-143
- Huang Y and Leung Y 2002 Analysing regional industrialisation in Jiangsu province using geographically weighted regression. *Journal of Geographical Systems* 4: 233-249
- Hurvich CM, Simonoff JS and Tsai CL 1998 Smoothing parameter selection in nonparametric regression using an improved Akaike Information Criterion. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)* 60: 271-293
- Jones K and Bullen N 1994 Contextual models of urban house prices: a comparison of fixed- and random-coefficient models developed by expansion. *Economic Geography* 70: 252-272
- Kim S 2003 Long-term appreciation of owner-occupied single-family house prices in Milwaukee neighborhoods. *Urban Geography* 24(3): 212-231
- Knox PL 1995 *Urban Social Geography: An Introduction*. London, Routledge

- Leung Y, Mei C-L and Zhang W-X 2000a Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A* 32: 9-32
- Leung Y, Mei C-L and Zhang W-X 2000b Testing for spatial autocorrelation among the residuals of the geographically weighted regression. *Environment and Planning A* 32: 871-890
- Maclennan D 1986 *Housing Economics: An Applied Approach*. London, Longman
- Maclennan D and Tu Y 1996 Economic perspectives on the structure of local housing systems. *Housing Studies* 11: 387-406
- Mason C and Quigley JM 1996 Non-parametric hedonic housing prices. *Housing Studies* 11: 387-406
- Massey DS and Denton NA 1988 The dimensions of residential segregation. *Social Forces* 67: 281-315
- Munro M and Lamont D 1985 Neighbourhood perception, preference, and household mobility in the Glasgow private housing market. *Environment and Planning A* 17: 1331-1350
- Orford S 2000 Modelling spatial structures in local housing market dynamics: a multilevel perspective. *Urban Studies* 37 (9): 1643-1671
- Paez A, Uchida T and Miyamoto K 2002a A general framework for estimation and inference of geographically weighted regression models: 1. location-specific kernel bandwidths and a test for local heterogeneity. *Environment and Planning A* 34: 733-754
- Paez A, Uchida T and Miyamoto K 2002b A general framework for estimation and inference of geographically weighted regression models: 2. spatial association and model specification tests. *Environment and Planning A* 34: 883-904
- Palm R 1978 Spatial segmentation of the urban housing market. *Economic Geography* 54: 210-221
- R Development Core Team 2004 R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria URL <http://www.R-project.org>
- Rosen S 1974 Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy* 82: 34-55
- Schnare A and Struyk R 1976 Segmentation in urban housing markets. *Journal of Urban Economics* 3: 146-166
- Straszheim M 1975 *An Econometric Analysis of the Urban Housing Market*. National Bureau of Economic Research, Cambridge, MA
- Tobler W 1970 A computer movie simulating urban growth in the Detroit region. *Economic Geography* 46: 234-240
- Watkins CA 2001 The definition and identification of housing submarkets. *Environment and Planning A* 33: 2235-2253
- Whitehead C 1999 Urban housing markets: theory and policy. In Mills ES and Cheshire P (eds.) *Handbook of Regional and Urban Economics*. Oxford, Elsevier Science
- WisconsinView 2004 WWW Document, <http://www.wisconsinview.org/>
- Wu C 2004 Normalized spectral mixture analysis for monitoring urban composition using ETM+ image. *Remote Sensing of Environment* In press
- Yu DL and Wu C 2004 Understanding population segregation from Landsat ETM+ imagery: a geographically weighted regression approach, *GIScience and Remote Sensing* 41: 145-164