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ABSTRACT

Wind power is the most important renewable energy source in many countries today, characterized by a rapid and extensive diffusion since the 1990s. However, it has also triggered much debate with regard to the impact on landscape and vista. Therefore, siting processes of wind farm projects are often accompanied by massive public protest, because of visual and aural impacts on the surrounding area. These mostly negative consequences are often reflected in property values and house prices. The aim of this paper is to investigate the impact of wind farms on the surrounding property values by means of a geographically-weighted hedonic pricing model. By comparing the predictive performance of standard Ordinary Least Squares (OLS) regression models and Geographically Weighted Regression (GWR) models, we find that, mainly due to a local clustering bias, global OLS estimation is inadequate for capturing the impacts of wind farm proximity on property prices. GWR reveals spatial non-stationarity of the variables and varying spatial patterns of the coefficient estimates across and within the city areas. Moreover, the GWR findings provide evidence for negative local effects of site proximity and of shadowing caused by wind turbines. The analysis was done for a study area in western Germany.

Keywords: Wind power, Hedonic pricing, Spatial non-stationarity, Geographically Weighted Regression

JEL Classification: C31, Q2, Q42, R31

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I. INTRODUCTION

Against the background of climate change and increasing scarcity of energy resources, the expansion of the renewable energy supply and the substitution of fossil fuel-based energy sources have become key topics on political agendas worldwide. Therefore, national energy policies are increasingly focusing on the promotion of wind, solar, biomass, geothermal, and other sources through extensive support schemes. As a result, the share of renewable sources has substantially increased in many countries since the 1990s. Although, the further expansion and promotion of renewable energies is crucial with regard to a substantial transition of the future energy mix, renewable energy projects often trigger public concern and resistance.

In Germany, considerable growth in the share of renewable energies is attributable to the introduction of the *Act of Granting Priority to the Renewable Energy Sources* (Erneuerbare-Energien-Gesetz, EEG) in 2000, amended in 2004, 2009, and 2012 (EEG, 2000, 2004, 2009, 2012). Introducing this regulatory framework for the promotion of electricity and heat from renewable energy sources (RES), which is essentially based on feed-in tariffs (FIT) guaranteed over 20 years, had a substantial impact on the speed and extent of the diffusion of renewable energy technologies. Particularly, the wind energy sector in Germany saw a rapidly increasing market share, with a total of 22,297 installed wind turbines (onshore and offshore) and an installed capacity of 29,075 MW by 2011 (Figure 1). Although wind energy already accounts for the highest share of electricity production within the renewable energy sector[1], its annual growth rate of installed capacity in 2011 of about 7% was still fairly high. Regarding the total electricity consumption in Germany in 2011, wind power accounted for 7.6%, which renders it the most important renewable energy source overall (BMU, 2012).

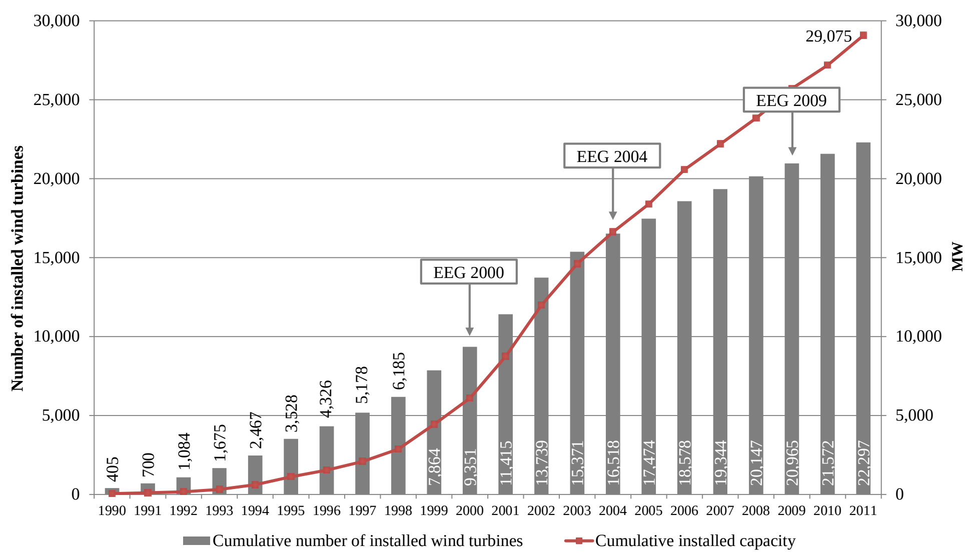

FIGURE 1
Development of the wind energy sector in Germany, 1990-2011
Source: BMU (2012), own illustration

[1] Wind energy accounted for 38.1%, biomass energy for 30.3%, hydro power for 16.0% and photovoltaics for 15.6% of the total amount of electricity produced by the renewable energy sector in 2011.

The extensively promoted expansion of renewable energy technologies is mostly justified by referring to the advantages and benign attributes associated with them. In the case of wind power, these attributes are, e.g., a “green” and CO_2-free energy generation without fuel costs as well as reasonable land consumption (Ackermann and Söder, 2002; Manwell, et al., 2009, pp.443-447; BWE, 2012). However, not only advantages and positive effects are associated with wind farm sites. Firstly, the amount of electricity produced is to some extent unreliable and unpredictable due to unsteady wind conditions. Secondly, the hub heights of wind turbines, both newly constructed and after repowering[2], have been increased over the last years in order to raise efficiency (Junginger et al., 2005; Sieros et al., 2012). As a consequence, the upscaling of wind turbine nacelles to heights of 100 m and more has led to a substantial change of landscape and vista.

The negative externalities caused by wind farm sites have led to major public concern that particularly refers to the impact on the environment and landscape. The latter tends to result in massive public protest, because of apparent visual[3] and aural[4] impacts on the surrounding area, with negative consequences that are supposed to be reflected in property values and housing prices. Public debates accompanying siting processes solely involve the argument of the expected devaluation of property or house prices as a consequence of siting in the proximity of a property or a house. Apart from the existing economic and regulatory complexity of siting processes, social acceptance and, especially in the case of wind farms, “NIMBY” (Not In My Backyard) attitudes become increasingly important (Wolsink, 2000; van der Horst, 2007; Wolsink, 2007). However, with decreasing social acceptance regarding siting decisions, the sound and transparent estimation and valuation of potential environmental impacts and other acceptance-biasing aspects should play a paramount role within the siting process in order to mitigate public protests and related unanticipated and underestimated project costs.

There have been a number of studies investigating the impact of wind farm sites on the surrounding area from a social acceptance point of view using survey-based approaches (e.g. Krohn and Damborg, 1999; Wolsink, 2000; Álvarez-Farizo and Hanley, 2002). The number of studies that aim at quantifying wind farm impacts are much less. Albeit there are a number of studies in this context using non-market valuation techniques, with the hedonic pricing approach most commonly being applied (e.g. Hoen et al., 2009; Canning and Simmons, 2010)[5], to our knowledge there are only four analyses in the peer-reviewed literature so far (Sims and Dent, 2007; Sims et al., 2008; Laposa and Mueller, 2010; Heintzelman and Tuttle, 2011) that will be briefly be discussed in turn.

Sims and Dent (2007) investigated the impact of a wind farm near Cornwall, UK, on house prices, using a hedonic pricing approach and comparative sales analysis. Applying

[2] Repowering is the replacement of older turbines in favor of new and more efficient ones, which most often also have a higher installed capacity.

[3] Visual impacts comprise general visibility and shadowing effects (Álvarez-Farizo and Hanley, 2002).

[4] Aural impacts refer to turbine noise and sound pressure (Rogers et al., 2006; Harrison, 2011).

[5] There is also research on the impact of wind farm proximity published in the form of project reports applying a simple quantitative approach (Sterzinger et al., 2003). They compared property transactions within a five-kilometer radius around the site, using a group of comparable control transactions outside of this range, but without controlling for other property price explaining factors.

straightforward OLS regression, they found some correlation between the distance to a wind farm and property values. Due to data limitations, the overall model results had a fairly weak explanatory power.

Sims et al. (2008) modeled the impact of wind farm proximity to houses for a region near Cornwall, UK. There was some evidence to suggest that noise and flicker effects as well as visibility may influence property value in a wind farm's vicinity. The hedonic analysis, in which standard OLS regression techniques were used, showed no significant impacts caused by the wind farm.

Laposa and Müller (2010) examined the impact of wind farm project announcements on property values for northern Colorado, US. Including observations before and after the announcement of the wind farm project, they applied a hedonic pricing model using standard OLS regression. The results obtained indicate a significant impact of the project announcement at the 10% level. However, they conclude that this impact is likely more attributable to the beginning of the national housing crisis rather than the announcement itself.

Exploring the impacts of new wind facilities on property values in northern New York, US by means of a fixed effects hedonic pricing model, Heintzelman and Tuttle (2011) found that nearby wind facilities can significantly reduce property values. Decreasing the distance to the wind farm to one mile indicated a property price devaluation of between 7.73% and 14.87%. In addition, they controlled for omitted variables and endogeneity biases by applying a repeat-sales analysis.

Table 1 provides an overview of selected hedonic pricing analyses on wind farm impacts.

TABLE 1
Overview of hedonic pricing studies

Study	Study area	*n*	Time period [years]	Pre-/Post-construction	Distance to wind farm [km]	Repeat sales	Property value impact
Sims and Dent (2007)	Cornwall, UK	919	5.5	post	< 16	no	negative
Sims et al. (2008)	Cornwall, UK	199	7.5	post	0.8-1.6	no	none
Laposa and Müller (2010)	Colorado, US	2,910	9	pre	< 80	no	none
Heintzelman and Tuttle (2011)	New York (state), US	11,331	10	pre/ post	< 86	yes	negative
Hoen et al. (2009)	US (ten study areas)	7,459	11.5	pre/ post	< 17.6	yes	none
Canning and Simmons (2010)	Ontario, Canada	83	2.5	post	n.a.	yes	none

Source: own illustration

The aim of this paper is to investigate the impacts of wind farms on the surrounding area through property values, by means of a geographically-weighted hedonic pricing model. The main focus lies on the investigation of visual impacts of wind farms, such as visibility and shadowing effects, as these are most often the central subject of public debates associated with siting processes. As most of the hedonic pricing studies on wind farms were conducted in the UK and the US, respectively, such a study investigating the impacts of wind farms in Germany can yield interesting new insights. Furthermore, in contrast to many hedonic pricing models, which are solely based on standard OLS estimation, our approach compares the explanatory performance of global and local estimation techniques[6] by means of Geographically Weighted Regression (GWR) analysis in order to improve the robustness of the results obtained. This particularly includes the consideration of spatial correlation and the analysis of the biasing influence of spatial non-stationarity on the global estimation results. The inclusion of a spatial weighting scheme is essential for the precision of the estimation. To our knowledge, there is no hedonic pricing analysis applied to wind farm impacts that specifically adopted a spatial estimation approach or emphasized the importance of local dependencies. Hence, the merit of our contribution is the specific investigation of spatial patterns and locational dependencies in the frame of a hedonic pricing model applied to the case of a wind farm site. A further improvement of our geographically-weighted hedonic pricing analysis over present hedonic pricing studies is achieved by applying Geographical Information System (GIS) techniques[7], which are adopted to derive space-related variables, such as distance measures and viewsheds[8] in a 3D environment on basis of high resolution geodata. A wind farm near the cities of Rheine and Neuenkirchen in the federal state of North Rhine-Westphalia (Germany), constructed in 2002, is chosen for conducting a pilot application of the model.

The remainder of this paper is organized as follows. Section 2 provides the theoretical background and literature overview. Section 3 introduces the hedonic pricing model and the estimation techniques applied. Furthermore, section 3 presents the dataset and the description of the estimation variables. Section 4 reports on the results obtained from global and local model specifications. Section 5 concludes and draws attention to future research needs.

II. THEORETICAL BACKGROUND AND RELATED LITERATURE

The methodology adopted in this paper is associated with non-market valuation techniques. These comprise various techniques for estimating the value of goods and services that are not traded in markets and which is, therefore, not revealed in market prices (Tietenberg and Lesiw, 2009, p.35). This applies particularly to environmental goods, such as air and water quality, as well as landscape and related positive or negative externalities.

There are different methods in the field of non-market valuation, which can be categorized according to the individuals' preferences that are either stated or revealed. *Stated preference methods*, such as contingent valuation or choice modeling, are based on practical survey techniques, essentially investigating the willingness to pay (WTP) for obtaining a particular good

[6] Besides a standard OLS estimation, we also apply a GWR in order to explore spatial non-stationarity. Local statistics based on GWR are treated here as spatial disaggregations of global statistics (OLS) (Fotheringham et al., 2002, p.6).

[7] GIS software is a powerful tool for enhancing the spatial precision of estimation techniques. With the capability to capture, store, manage, analyze, and display space-related information, GIS software systems are frequently used for underpinning hedonic pricing models. In this context, implementation possibilities are quite diverse, such as analyzing spatial heterogeneity (Geoghegan et al., 1997) or developing Digital Elevation Models (DEM), in order to apply visibility analyses (Paterson and Boyle, 2002; Lake et al., 2010).

[8] Viewsheds display areas of land, water, or other environmental elements that are visible to the human eye from a fixed vantage point (in our case the concerned properties). The visibility of a large-scale wind farm in the close vicinity of a property might have a significant impact on its value.

(Kriström, 2002; Bateman, 2010; Tisdell, 2010, p.203; Krueger et al., 2011). Alternatively, *revealed preference methods* ground on the assumption that individuals' preferences can be derived from their consumption behavior (Tietenberg and Lesiw, 2009, p.39; Tisdell, 2010, p.203), and comprise methods like the travel cost method and the hedonic pricing method.

Rosen (1974) pioneered the economic formalization of a hedonic pricing model, although earlier studies tackled the approach of implicit markets (Tiebout, 1956) and statistical relationships between air quality and housing values (Ridker and Henning, 1967). According to Rosen (1974), hedonic pricing models seek to explain the overall price $p=p(x)$ of a differentiated product that is characterized by a bundle of n attributes $x = (x_1,\ldots, x_n)$. The hedonic function, therefore, results from the market interaction of demand and supply. Product differentiation implies the availability of alternative bundles, so that in market equilibrium, p equals each consumer's bid for the differentiated product (Rosen, 1974).

In the field of environmental economics, hedonic pricing models are widely used to estimate the WTP for improvements in environmental goods (Palmquist, 2002), most frequently applied to the housing or property market. Houses or properties are compound products, characterized by sets of structural (e.g. house/lot size, age, and type of building), neighborhood (e.g. income distribution, crime rate, and taxes), spatial (e.g. distances to local amenities or disamenities) and environmental (e.g. noise levels, air quality, and vista) attributes. The functional form of the price is monotonically increasing in desirable characteristics, whereas it remains silent about the correct relationship between the price and the characteristics (Palmquist, 2002).

Hedonic studies show a wide range of application fields. Commonly investigating air quality (Nelson, 1978; Kim et al., 2003; Chay and Greenstone, 2005), water quality (Steinnes, 1992; Leggett and Bockstael, 2000; Poor et al., 2007), noise (Espey and Lopez, 2000; Theebe, 2004; Baranzini and Ramirez, 2005; Dekkers and van der Straaten, 2009) and proximity to hazardous facilities (Kohlhase, 1991; Nelson et al., 1992; Simons et al., 1997), hedonic models are, moreover, increasingly applied in the field of energy and the environment (Gamble and Downing, 1982; Clark et al., 1997; Clark and Allison, 1999; Des Rosiers, 2002). While the number of studies on the impact of renewable energy technologies, including wind farms, is increasing, still only few peer-reviewed articles exist.

III. HEDONIC PRICING MODEL

Many hedonic pricing studies that investigate the impacts of energy facilities use straightforward OLS estimation. In our estimations, we compare OLS estimates with those obtained from GWR. GWR accounts for spatially-varying relationships in the dataset. Details on the estimation procedures are provided in the following.

Estimation methods

The hedonic pricing model estimated in a semi-log specification is given by:

$$\ln p_i = \alpha + \beta S_i + \gamma N_i + \tau G_i + \varepsilon_i \quad , \qquad [1]$$

where ln$p$ is the log of the property price, S denotes a vector of structural characteristics with $S = \{s', \ln s''\}$, where s' (s'') does not enter (does enter) the regression in the log scale, N is a vector of neighborhood characteristics, G denotes a vector of GIS-measured spatial variables with $G = \{g', \ln g''\}$, where g' (g'') does not enter (does enter) the regression in the log scale, α, β, γ and τ represent the parameters to be estimated, ε is the error term, and i the observation concerned. The semi-log specification is a commonly used regression form in hedonic pricing studies (Clark and Allison, 1999; Baranzini and Ramirez, 2005; Heintzelman and Tuttle, 2011), which allows for an intuitive interpretation of the results. The estimated coefficients can be interpreted as elasticities if the independent variable enters the model in the log scale and as semi-elasticities if the variable does not enter in the log scale (Gujarati and Porter, 2009, p.162). In the case where the independent variable is a dummy variable, the coefficients are interpreted as median impacts (Gujarati and Porter, 2009, p.298). In addition, using a semi-log regression form often reduces heteroscedasticity (Gujarati and Porter, 2009, p.394).

As hedonic pricing studies are based on spatial data, describing the possible relationship between property prices and the considered explanatory variables in a certain environment, this data contains both attribute and locational information (Fotheringham et al., 2002, p.3)[9]. In this context, estimations provided by a global OLS model might be inadequate in capturing spatially-varying relationships, as global statistics are only describing average relations between property values and the considered variables. But there may be local differences in the determinants of property prices across the study area. In consequence, with increasing spatial variation of the local observations, the reliability of the global model estimates decreases (Fotheringham et al., 2002, p.2). A spatial variant of Simpson's Paradox, illustrated in Figure 2, reveals the problematic nature of the often very limited predictive power of global estimates in capturing local relationships (Simpson, 1951; Fotheringham et al., 2002, p.8).

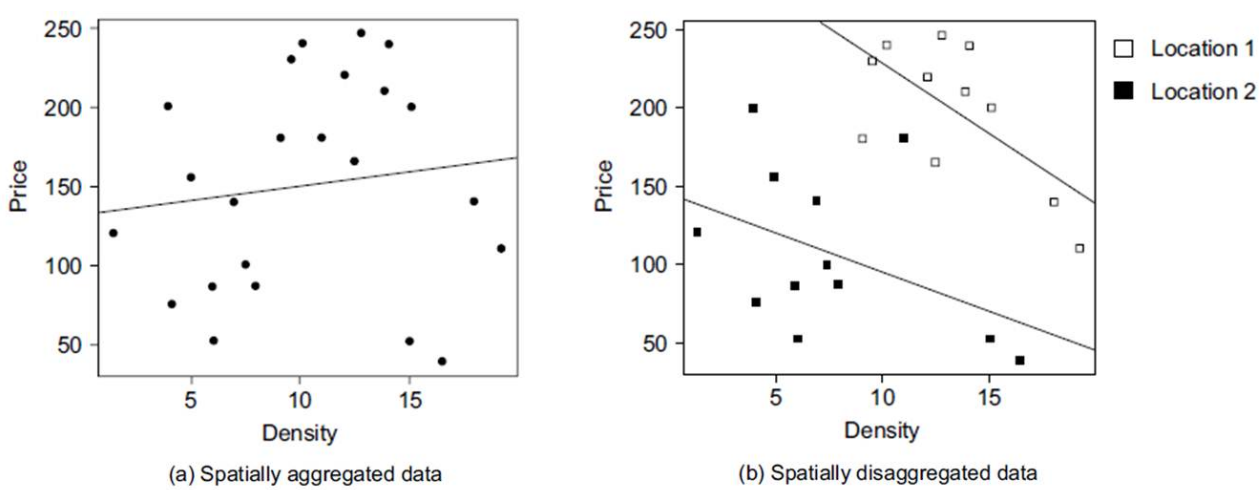

FIGURE 2
A spatial variant of Simpson's Paradox
Sources: Simpson (1951); Fotheringham et al. (2002, p.8)

[9] Aspatial data, such as data on a firms' production output plotted against the number of employees, comprise attribute information only.

Simpson's Paradox regards the differences in the results obtained when datasets are analyzed in a spatially aggregated or disaggregated form. In Figure 2, house prices are plotted against population density. The spatially aggregated data contains combined information of different locations that show a positive relationship. The spatially disaggregated data differentiate between two locations and find a negative relationship for both locations. The danger of analyzing aggregate datasets refers to the presence of spatial non-stationarity, as the measurement of a relationship depends on where the measurement is taken (Fotheringham et al., 2002, p.9). Against the background of spatial non-stationary relationships within the data, we also estimate our hedonic pricing model by means of a GWR. This appears particularly useful, as our dataset on property prices includes two different cities with two separate districts affected in each city. There might be spatial dependencies that refer to attribute values in one location, which might depend on values of the attributes in neighboring locations (Anselin and Getis, 2010). One spatial dependence measure is Moran's Index (Moran's *I*) for spatial autocorrelation (Anselin and Getis, 2010). In terms of property market data, spatial autocorrelation refers to a situation where properties with high values are generally located in close proximity to other properties of comparable value and low-value properties are also clustered. An estimation of local spatial autocorrelation through a GWR was introduced by Brunsdon et al. (1998). They applied the theoretical foundation of GWR to the Ord model[10] (Ord, 1975), and demonstrated the problems of spatial association of relying on global models with an empirical example on owner-occupation in the housing market in two cities in northeast England.

The hedonic pricing estimation on the basis of the global OLS function given in [1] is now specified in terms of a GWR, thus allowing for the estimation of local parameters:

$$\ln p_i = \alpha_i(u_i, v_i) + \beta(u_i, v_i)S_i + \gamma(u_i, v_i)N_i + \tau(u_i, v_i)G_i + \varepsilon_i \ , \qquad [2]$$

where (u_i,v_i) indicates the coordinates of the i^{th} observation. Note that eq. [1] represents a special case of eq. [2], in which the considered parameters are assumed to be spatially invariant (Fotheringham et al., 2002, p.52). Following Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970), the GWR has to be calibrated in a way that observations near to observation *i* have more influence on the estimation of the parameters ($\alpha_i(u_i,v_i)$, $\beta_i(u_i,v_i)$, $\gamma_i(u_i,v_i)$, $\tau_i(u_i,v_i)$) than data located farther away from *i*. The calibration of the model is set by spatial kernels which can be fixed or adaptively fitted to the spatial distribution of the regression points. Figure 3 graphically illustrates a spatial kernel and a GWR with adaptive spatial kernels.

[10] Ord (1975) proposed an autoregressive moving-average (ARMA) model in order to capture spatial correspondences in the variables and residuals, respectively.

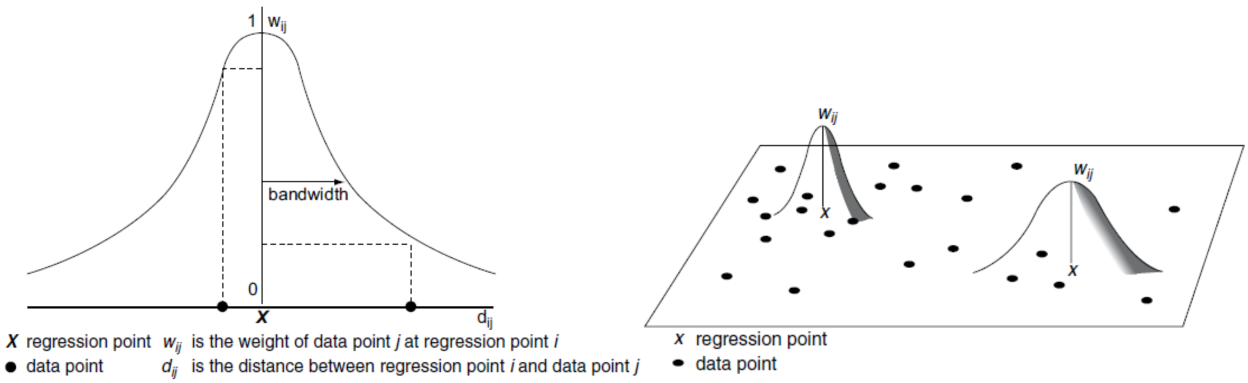

FIGURE 3
A spatial kernel and a GWR with adaptive spatial kernels
Source: Fotheringham et al. (2002, pp.44 and 47)

The estimation of the parameters for each location depends on the particular weighting function chosen in order to capture the spatial differences in a certain area. According to the weighting function and its bandwidth, the weight of the data point w_{ij} decreases with increasing distance to the regression point d_{ij}. The definition of the optimal bandwidth of the weighting function is crucial for the precision of the GWR. Therefore, it might be useful not to assume fixed spatial kernels with fixed bandwidth for each regression point, but rather adaptive kernels that take account of differing density of data points around regression point i (Figure 3).

In order to determine the optimal spatially-varying weighting method, we adopt an adaptive kernel that uses an Nth nearest neighbor weighting of point i with a bi-square decay function. Following Fotheringham et al. (2002, p.58), that is,

$$w_{ij} = \begin{cases} [1-(d_{ij}/b)^2]^2 \text{ if } j \text{ is one of the } N\text{th nearest neighbors of } i \text{ and} \\ b \text{ is the distance to the } N\text{th nearest neighbor} \\ 0 \text{ otherwise.} \end{cases} \qquad [3]$$

The determination of the weighting function and optimal bandwidth selection was obtained by minimizing the corrected Akaike Information Criterion (AIC_c) (Fotheringham et al., 2002, p.61). The AIC_c for GWR defined as:

$$AIC_C = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left\{\frac{n+tr(S)}{n-2-tr(s)}\right\}, \qquad [4]$$

where n denotes the sample size, $\hat{\sigma}$ the estimated standard deviation of the error term and $tr(S)$ the trace of the hat matrix, which is a function of the bandwidth (Fotheringham et al., 2002, p.61). The AIC_c is used to assess whether GWR provides a better fit than the global OLS model.

The next subsection gives an overview of the data used and the study area considered.

The data

Investigating the impact of a wind farm site on surrounding property values, this study focuses on property sales within an area of 119 km^2 in the north of the federal state of North Rhine-Westphalia, including parts of the city of Rheine and the city of Neuenkirchen. Both cities, at least two districts in the case of Rheine (Mesum and Hauenhorst), are in the immediate proximity of the considered wind farm site. This northern region of North Rhine-Westphalia can be defined as a semi-urban region mainly characterized by medium- and small-sized towns.[11] In 2011, a population of 26,900 lived within a radius of about 5.5 kilometers around the site.

In 2000, the federal district administration announced the construction of a wind farm consisting of nine turbines, which was finally built in July 2002. The nine turbines, each with a capacity of 1.5 MW, have hub heights of 100 meters and rotor sizes of 77 meters. Particularly in view of the fact that this area of northern North Rhine-Westphalia is very flat regarding its relief, with an average altitude only varying between 30 and 90 m above sea level, the wind farm substantially influences the landscape. Figure 4 illustrates the study region and the location of the wind farm site.

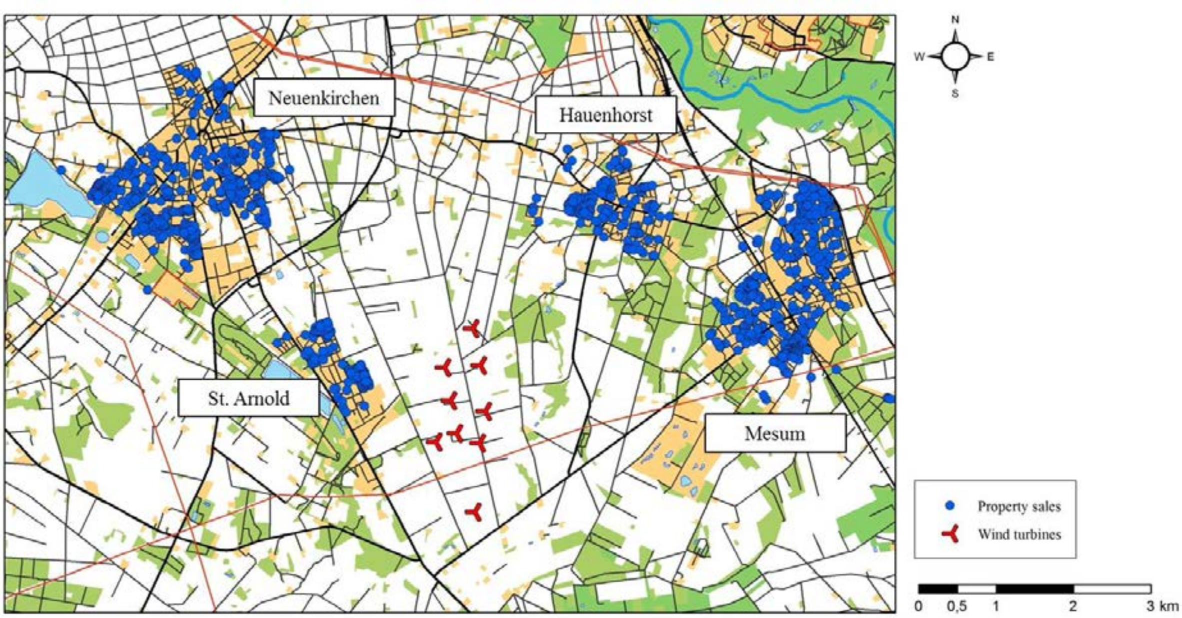

FIGURE 4
Study area
Source: Own illustration, based on data provided by the Geodatenzentrum NRW (2011)

[11] The definition of town-size categories for German cities is taken from Bähr and Jürgens (2005). According to their categorization, towns with a population of about 2,000 to 5,000 are small rural towns, cities with a number of inhabitants ranging from 5,000 to 20,000 are small-sized cities, cities with 20,000 to 100,000 inhabitants are medium-sized cities and large cities are defined by comprising more than 100,000 inhabitants. The city of Rheine is a medium-sized town with an overall population of about 76,500 in 2011 (IT.NRW, 2012). In 2011, Mesum's population was about 8,400 and Hauenhorst had about 4,500 inhabitants. The city of Neuenkirchen is a small-sized town with about 14,000 inhabitants in 2011 (IT.NRW, 2011). Corresponding to Neuenkirchen is also the village of St. Arnold (population about 3,000), which is about one kilometer away from the actual city area in a northerly direction.

Property market data for the two cities contained 1,405 property sales within the period of 1992 until 2010 and was provided by the Expert Advisory Boards (*Gutachterausschüsse*) of the federal district of Steinfurt[12] and the city of Rheine. The dataset included the sales prices of the properties, lot sizes, sales dates, and the address-based location. All property prices in the dataset were deflated by the German Construction Price Index, with 2005 as the base year (German Federal Statistical Office)[13]. The distance of the observations to the wind farm site ranges between 945 m to 5,555 m, so that, compared to other hedonic studies (cf. Table 1), the properties are very close to the site. Table 2 gives an overview of the observations and their distribution according to city districts, wind farm announcement, construction, and type of sale.[14]

TABLE 2

Summary statistics – Property sales in the study area, 1992-2010

	n	Percentage
Total no. of observations	1,405	100.0
Hauenhorst	220	15.7
Mesum	470	33.5
Neuenkirchen	556	39.5
St. Arnold	159	11.3
Sales	1,202	85.6
Re-sales	203	14.4
Pre-announcement	766	54.5
Sales pre-announcement (excl. re-sales)	655	54.5
Post-announcement	639	45.5
Sales post-announcement (excl. re-sales)	547	45.5
Pre-construction	872	62.1
Sales pre-construction (excl. re-sales)	750	62.4
Post-construction	533	37.9
Sales post-construction (excl. re-sales)	452	37.6

A major difference to most of the hedonic pricing studies in the literature is the usage of property values, i.e. prices of parcels of land, and not house prices. This is mainly due to data availability issues and privacy restrictions of address-based house price data in Germany. Nevertheless, we assume that properties are likewise suitable for conducting a hedonic pricing study, as their values are also sensitive to changes of the surrounding location. Only the selection of the structural variables differs compared to hedonic pricing studies using house prices.[15] Furthermore, in our study, we only consider developed and undeveloped properties for residential utilization.

[12] Rheine and Neuenkirchen are cities that both belong to the federal district of Steinfurt.

[13] Available online at https://www.destatis.de/EN/FactsFigures/Indicators/ShortTermIndicators/Prices/bpr110.html. (accessed January 14, 2012)

[14] Table A1 in the Appendix provides a more detailed overview of the observation summary.

[15] Hedonic pricing studies using house prices include structural variables, such as the number of rooms, the age of the house, or the availability of a garage, which are irrelevant for properties in terms of parcels of land.

TABLE 3
Descriptive statistics

	Variable	Units	Mean	Std. dev.	Min	Max
Structural	ln *p*	ln €	10.43	0.84	4.34	12.59
	ln *Lot size*	ln m²	6.18	0.70	1.10	9.83
	Ground value	€/m²	81.55	19.26	15	123
	Type single-family house	dummy	0.55	0.50	0	1
	Type duplex house	dummy	0.17	0.38	0	1
	Type row house	dummy	0.02	0.15	0	1
	Type multi-family house	dummy	0.02	0.15	0	1
	Type untilled parcel	dummy	0.23	0.42	0	1
	Waterfront	dummy	0.00	0.07	0	1
	Neuenkirchen	dummy	0.40	0.49	0	1
	St.Arnold	dummy	0.11	0.32	0	1
	Hauenhorst	dummy	0.16	0.36	0	1
	Mesum	dummy	0.33	0.47	0	1
Neighborhood	ln *Income*	ln €	9.66	0.11	9.49	9.85
	Unemployment	%	9.38	2.08	4.9	12.8
	Crime	criminal offenses/ 1,000 cap.	60.89	15.78	37.38	86.97
	Real estate tax	millage rate	303.84	51.97	255	401
	Immigrants	%	6.09	0.76	5.22	7.23
	Population density	inhabitants/km²	328.34	58.258	246	411
Spatial	ln *Wind farm*	ln *m*	8.04	0.45	6.89	8.57
	Distance < 2 km	dummy	0.12	0.33	0	1
	Distance 2-3 km	dummy	0.20	0.40	0	1
	Distance > 3 km	dummy	0.68	0.47	0	1
	Visibility	dummy	0.29	0.46	0	1
	No. of visible turbines	-	0.77	1.48	0	7
	Shadowing	dummy	0.05	0.22	0	1
	Post-announcement	dummy	0.45	0.50	0	1
	Post-construction	dummy	0.38	0.49	0	1
	ln *Railroads*	ln *m*	7.53	1.28	3.54	8.91
	ln *Train station*	ln *m*	8.00	1.12	4.18	9.18
	ln T*ransmission line*	ln *m*	6.85	0.74	3.47	7.72
	ln *Major road*	ln *m*	5.25	0.89	2.11	6.72
	ln *Road*	ln *m*	2.48	0.42	0.02	4.53
	Street noise	classes	1.07	0.38	1	5
	ln *CBD*	ln *m*	6.85	0.99	1.26	8.28
	ln *Commercial area*	ln *m*	7.36	0.88	3.71	8.65
	ln *Supermarket*	ln *m*	6.28	0.60	3.52	7.45
	ln *Forest*	ln *m*	5.30	0.82	1.61	6.54
	ln *River*	ln *m*	8.03	0.75	6.41	8.97
	ln *Lake*	ln *m*	6.40	0.73	3.23	7.52
	ln *Natural reserve*	ln *m*	7.73	0.70	5.53	8.64
	ln *1st school*	ln *m*	6.35	0.52	4.25	7.54
	ln *2nd school*	ln *m*	6.88	0.65	3.79	8.15

Table 3 gives an overview of the 42 explanatory variables that were tested in different model specifications in order to explain the variation in the property prices. The different model specifications accrue from the dataset used, which contains property market data before and after the construction of the wind farm. Therefore, one model is specified in a way that it only includes property sales after the construction of the wind farm, focusing on the influence of distance and visibility effects. Alternatively, another model specification involves all property sales in the period from 1992 to 2010, investigating the wind farm project announcement and construction effects. The model specifications are presented in detail in Section 4.

The structural variables, such as the sales price, lot size, and the district dummy variables, were taken from the property sales dataset provided by the Expert Advisory Board. The ground value[16], property type[17] and waterfront value were derived using data services of the Topographic Information Management of the federal state of North Rhine-Westphalia (Topographisches Informationsmanagement NRW).[18] Most importantly, we expect a highly positive relationship between the property price and the lot size.

We used various data sources to assemble the group of neighborhood variables, mainly from statistical offices on the state, district, and city level.[19] All neighborhood variables vary only over time and the four different city districts. Neighborhood data in a higher resolution, i.e. different values for each observation, are not available. This might result in a limited scope for interpretation of these neighborhood variables in the results obtained. Nevertheless, one might expect negative effects of high rates of unemployment, immigrants and crime as well as a high real estate tax, and a positive impact of higher average income.

The set of spatial variables predominantly includes Euclidean distance measures from each observation to various features in the considered area, which characterize the location for each property. All distance variables were calculated using GIS software.[20] Furthermore, we additionally included dummy variables, particularly in order to measure wind farm-related impacts. The dummy variables *Post-announcement* and *Post-construction* base on the date of the wind farm project announcement (June 2000) and date of the wind farm construction (August 2002). The main focus within the set of spatial variables lies on the distance, shadowing, and visibility variables, which were compiled using GIS tools. Besides the Euclidean distance measure from each property to the wind farm, we also tried to identify distance effects within the first two kilometers around the wind farm and above by means of dummy variables. Negative environmental effects often associated to wind farm sites refer to the shadowing effect caused by the rotor blades in relation to the position of the sun (Hau, 2006). In order to capture the

[16] The ground value is an average local ground value that is determined on the basis of purchase prices of properties with respect to the development status. The ground value is only available for city districts or streets. It is included in the model for consistency reasons, because it should be positively related to the property prices.

[17] The property type is defined according to its development that could be a single-family house, a duplex house (two-family house), a row house, a multi-family house, or an untilled parcel, respectively.

[18] Available online at http://www.tim-online.nrw.de/tim-online/nutzung/index.html. (accessed February 2, 2012)

[19] The data was obtained upon request from the federal statistical office of North Rhine-Westphalia, the federal district administration of Steinfurt and the city administration of Rheine and Neuenkirchen.

[20] We used the ESRI ArcGIS Desktop software package (Version 9.3.1), including the Spatial Analyst Tool, Spatial Statistics Tool, and the 3D Analyst Tool.

shadowing effects caused by the rotor blades, we determined the potentially affected areas, taking into account the heights of the turbine, the rotor blade diameter and the positions of the sun during a day. Identifying the affected areas, we were able to determine the presence of the shadowing effect for each property. To measure the visibility of the wind farm site, we calculated viewsheds for each property. Viewsheds refer to the visible area from an observer's perspective, in our case from a property. A precise measurement of the view crucially depends on capturing all features in the landscape that are visible from the observer's point of view. The view of a certain feature in the landscape might be hindered by heights, slopes, vegetation, or buildings. In order to calculate viewsheds as precisely as possible, we applied a digital surface model[21] with an accuracy of one meter, which was provided by the Geodatenzentrum NRW.[22] The digital surface model included height level information of the terrain, the vegetation, and buildings, and allowed us to calculate a raster of the area terrain. On the basis of raster data we were able to conduct a viewshed analysis using the ESRI ArcGIS Spatial Analyst and 3D Analyst tool. Figure 5 illustrates the results of the viewshed analysis, indicating the areas with a view of the wind farm. Overall, for 128 properties in the dataset at least one turbine was visible.[23] Besides a simple visibility dummy, we also tested a variable that accounts for the number of visible turbines.

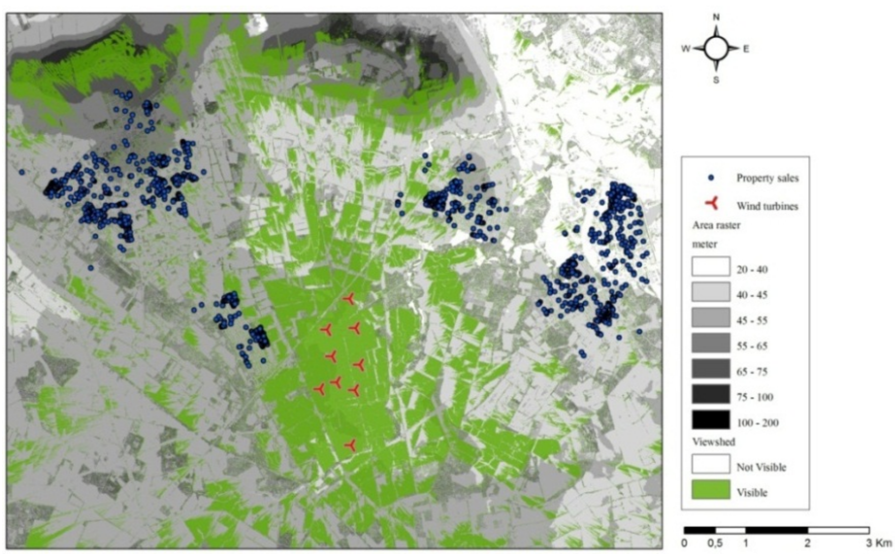

FIGURE 5
Visibility analysis
Source: Own calculation and illustration, based on data provided by the Geodatenzentrum NRW (2011)

[21] The digital surface model is essentially based on multipoint information that contains x and y coordinates as well as the z-value, referring to longitude, latitude, and height. The surface model for the whole study regions consists of about 120 million data points. For reasons of data operability, the multipoint surface information was converted into a surface raster. Raster data on surface information correspond to a surface as a grid of equally sized cells that comprise the attribute values for representing the x and y coordinates and the z-value.

[22] The Geodatenzentrum NRW provides geodata on the basis of the ordnance survey. Available online at www. geodatenzentrum.nrw.de/. (accessed November 2, 2011)

[23] The visibility analysis only included properties that were sold after the construction of the wind farm.

Aural impacts of wind turbines that result in an increase of the dB-level above the average ambient noise level in urban or semi-urban regions[24] are only measureable within the immediate vicinity of a turbine of about 350 m (Hau, 2006; Rogers et al., 2006; Harrison, 2011). As in our case the shortest distance to a property is 945 m, aural impacts are not considered.

IV. RESULTS

In this section, we compare the results of global OLS and local GWR estimations, focusing on the impact of wind farm proximity. Firstly, we applied three different OLS model specifications with regard to the selected variable and the data samples used. Secondly, we compare these results to those obtained by GWR estimations.

Global model

Before estimating the OLS regressions, we excluded the 203 property re-sales from the overall dataset. One reason for exclusion is to prevent serial autocorrelation in the global model due to different values for properties at different points in time. Another reason refers to spatial autocorrelation in the case of the local model that can be caused because of identical information in the concerning location (Heintzelman and Tuttle, 2011).

We applied three different global model specifications. The first two models (referred to as 1A and 1B) include 452 properties that were sold after the construction of the wind farm. This allows for investigation of the specific environmental impacts of wind turbines, such as visibility and shadowing effects. The major difference between models 1A and 1B is that we tested a distance measure (ln *Wind farm*) in model 1A, which was then substituted by distance dummies (*Distance < 2 km*, *Distance 2-3 km* and *Distance > 3 km*) in model 1B. Model 2 contained the overall dataset with 1,202 observations. In this case the focus was on the impact of the announcement and construction of the wind farm, which was tested by applying a *Post-announcement* and a *Post-construction* dummy variable, respectively.

The explanatory power of the global OLS models 1A and 1B was reported with an R^2 of 0.813 and 0.815, respectively, and, therefore, indicated a fairly good model fit in both cases. The application of the Durbin-Watson test indicated no presence of autocorrelation. Several variables had to be excluded from the models due to the appearance of multicollinearity that was controlled for by using the variance inflation factor (VIF). Particularly the district dummies showed high VIFs due to correlation with a few distance measures. In addition, most of the neighborhood variables, such as *Population density*, *Crime*, *Real estate tax*, *Immigrants* and *Unemployment*, had to be excluded due to multicollinearity. This could be attributed to the limited variation within the neighborhood data available and also to the data sample size in case of models 1A and 1B. Furthermore, due to correlation among the distance measures, we removed the variables ln *Train station*, ln *Forest*, ln *River*, ln *Lake* and ln *Natural reserve*. Also the property type variables had to be removed for multicollinearity reasons. The implementation of the White test indicated

[24] The average noise level in urban areas is 55 dB during the day and 40 dB at night, respectively. In semi-urban or rural areas these values range between 50 dB during daytime and 35 dB at night, respectively (Hau, 2006).

heteroskedasticity, so that we applied heteroskedasticity-consistent standard error (HCSE) estimators in the global OLS regressions (Hayes and Cai, 2007). The OLS estimation results for the model specifications 1A and 1B are summarized in Table 4.

TABLE 4

Global model - OLS estimation results for model specifications 1A and 1B

Model 1A		**Model 1B**	
Variable	**OLS (HCSE)**	**Variable**	**OLS (HCSE)**
Intercept	2.446 (3.750)	*Intercept*	2.131 (3.698)
ln *Lot size*	.973*** (.072)	ln *Lot size*	.977*** (.074)
Ground value	.003 (.003)	*Ground value*	.002 (.003)
Waterfront	.225** (.089)	*Waterfront*	.270*** (.084)
ln *Income*	.104 (.393)	ln *Income*	.328 (.405)
Street noise	-.068** (.030)	*Street noise*	-.091*** (.029)
Visibility	-.003 (.029)	*Visibility*	-.008 (.028)
Shadowing	-.098* (.063)	*Shadowing*	-.084* (.053)
ln *Wind farm*	.209*** (.074)	*Distance < 2 km*	-.252*** (.096)
		Distance 2-3 km	.026 (.083)
ln *Railroads*	.051 (.036)	ln *Railroads*	.079* (.042)
ln *Major road*	.039* (.022)	ln *Major road*	.026 (.023)
ln *Road*	-.079 (.058)	ln *Road*	-.082 (.058)
ln *CBD*	.012 (.026)	ln *CBD*	.004 (.027)
ln *Commercial area*	.000 (.045)	ln *Commercial area*	.022 (.045)
ln *Supermarket*	-.202*** (.052)	ln *Supermarket*	-.155*** (.051)
ln *Transmission line*	.004 (.035)	ln *Transmission line*	-.025 (.035)
ln *1st school*	-.061 (.047)	ln *1st school*	-.058 (.046)
ln *2nd school*	.064 (.040)	ln *2nd school*	-.008 (.056)

Note: Standard errors are reported in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Most of the results correspond to the expectation with regard to positive or negative significance. The variable ln *Lot size* turned out to be the most important determinant of the property price, with an estimated coefficient of .973 and .977, respectively, at the 1% significance level. Therefore, a one percent increase in lot size results in an increase of approximately 0.97% in property price. A positive impact on property values is caused by the availability of a waterfront (.225 at the 5% level and .270 at the 1% level, respectively) and the proximity to a supermarket (-.202 and -.155, respectively)[25], whereas street noise (-.068 at the 5% level and -.091 at the 1% level) impacts the property value negatively. The variable ln *Income* turned out to be insignificant due to the limited variation and sample size in cases 1A and 1B. The proximity to railroads, which is also frequently investigated by means of hedonic pricing studies (Bowes and Ihlanfeldt, 2001; Theebe, 2004), appeared insignificant in case of model 1A and negatively significant in model 1B, but only at the 10% level (.079).

The wind-farm-related variables showed consistent results in terms of significance and signs. Most importantly, according to the global OLS results in model 1A, the proximity to a wind farm negatively affects the property price (.209). In other words, a one percent increase in distance to the wind farm increases the price by about 0.209%, vice versa proximity decreases the price. Substituting the distance measure in model 1A by distance dummies yields comparable results. Thus, proximity to the wind farm negatively affects the property values within the first two kilometers (-.252). The dummy variables for the distances above two kilometers did not turn out to be significant. The dummy variable capturing the effect of the wind farm's shadowing area indicated a negative impact (-.098 and -.084, respectively), whereas only at the 10% level. Finally, the visibility variable turned out to be insignificant in both cases, indicating that the view of the wind farm does not affect the property price according to the OLS estimates.

The explanatory power of model 2 was reported with an R^2 of 0.887, indicating a very good model fit, even higher compared to the first model specifications. Again the Durbin-Watson test reported the absence of autocorrelation. Also, the testing for multicollinearity mostly led to the removal of the same variables as in models 1A and 1B. Due to the higher sample size, the property type variables (*Type duplex house* and *Type untilled parcel*), the variable *Unemployment* and the two distance measures, ln *Forest* and ln *Lake* were included into the model, as no indication of multicollinearity was found anymore. Following the White test for heteroskedasticity, we again applied HCSE estimators in the OLS regression to control for biased standard errors and significance levels due to heteroskedasticity. The results for model 2 are reported in Table 5.

Compared to the first two model specifications, many variables show similar impacts on property prices. Again ln *Lot size* is the most important determinant of property values (1.057). Although having slightly different significance levels, the variables *Street noise*, ln *Railroads* and ln *Supermarket* show comparable estimation results. But in the case of model 2 a few more variables turn out to influence the property values, which might be attributable to the larger

[25] The variable ln S*upermarket* showed a negative coefficient, but proximity positively impacts the property price. A one percent increase in distance to a supermarket results in a -.202 and -.155, respectively, decrease in price; vice versa proximity increases price.

sample size. As expected, *Ground value* and ln*Income* show a positive influence on property prices (.001 and .260, respectively). The variable *Unemployment* is the only variable that works contrary to prior expectations and is quite counterintuitive (.071) by indicating a positive impact on property values. This might be traced back to the data availability and limited data resolution. The development status of a property also seems to impact its value positively with regard to the duplex house type (.106) and negatively regarding the untilled parcel type (-.190). An increasing distance to the next road and the commercial area negatively affects the property value (-.081 and -.044), i.e. proximity to useful infrastructure is positively related and likely reflects a higher degree of accessibility.

TABLE 5
Global model - OLS estimation results for model specification 2

Model 2			
Variable	**OLS (HCSE)**	**Variable**	**OLS (HCSE)**
Intercept	-15.209*** (2.029)	ln *Railroads*	.041** (.018)
ln *Lot size*	1.057*** (.026)	ln *Major road*	.005 (.014)
Ground value	.001** (.001)	ln *Road*	-.081*** (.026)
Waterfront	.159 (.365)	ln *Forest*	.017 (.021)
Type duplex house	.106*** (.020)	ln *Lake*	.034** (.016)
Type untilled parcel	-.190*** (.034)	ln *CBD*	-.034 (.021)
ln *Income*	.260*** (.210)	ln *Commercial area*	-.044** (.018)
Unemployment	.071*** (.010)	ln *Supermarket*	-.046* (.024)
Street noise	-.063*** (.020)	ln *Transmission line*	-.013 (.024)
Post-announcement	-.028 (.043)	ln *1st school*	-.022 (.025)
Post-construction	-.054* (.035)	ln *2nd school*	-.041 (.034)

Note: Standard errors are reported in parentheses.
***, ** and ** indicate significance at the 1%, 5% and 10% level, respectively.

The wind-farm-related variables in model 2 allowed us to investigate the impact of the wind farm project announcement and construction by means of dummy variables. According to the results reported in Table 5, the variable *Post-announcement* was not significant. Therefore, according to the OLS results, we find no evidence for an announcement effect. Alternatively, the construction of the wind farm is negatively related to the property price (-.054), albeit only at the 10% level.

According to the global estimates, it seems obvious to deduce that wind farm presence is significantly influencing the surrounding property prices, as these were especially the findings from models 1A and 1B. The next subsection examines the importance and biasing influence of spatial variations in the dataset.

Local model

A general test for spatial autocorrelation in the OLS residuals using Moran's *I* clearly reveals significant local clustering, which, therefore, provides evidence of the need for further investigations on spatial dependencies. Moran's *I*, generally, ranges from -1 in the case of negative autocorrelation to +1 in the case of positive autocorrelation, with values of 0 indicating the absence of autocorrelation (Cliff and Ord, 1981). Moran's *I* and related *p*-values for the residuals of the three OLS model specifications compared to the GWR models are reported in Table 6.

TABLE 6
Moran's I for OLS and GWR model specifications

		Moran's *I*	***p*-value**
Model 1A	OLS (HCSE)	.092	.000
	GWR	.003	.752
Model 1B	OLS (HCSE)	.031	.034
	GWR	.003	.765
Model 2	OLS (HCSE)	.081	.000
	GWR	.048	.000

In the case of all OLS models, Moran's *I* indicates positively significant autocorrelation of the residuals. Moran's *I* of the GWR models in comparison shows a substantial improvement with index values close to 0, thus indicating less or no autocorrelation. Also, the *p*-values are insignificant in the case of models 1A and 1B. Model 2 in the GWR specification shows substantial improvement regarding the level of autocorrelation, but the *p*-value remains significant. Table 7 gives an overview of the general model performance of the OLS compared to the GWR estimations according to the AIC_c, R^2, degrees of freedom (DF), and *F*-test.

TABLE 7

AIC_c, R^2, degrees of freedom (DF) and *F*-value for OLS and GWR model specifications

	Method	**AIC_c**	**R^2**	**DF**	***F***
Model 1A	OLS	172.57	0.813	17	1.569***
	GWR	28.41	0.887	330	
Model 1B	OLS	169.22	0.815	18	1.678***
	GWR	30.92	0.885	335	
Model 2	OLS	390.26	0.887	21	4.324***
	GWR	275.38	0.904	1143	

*** indicates significance at the 1% level.

As can be seen, according to the AIC_c and R^2, the model performance in all cases is substantially improved when applying the GWR method[26]. The *F*-tests according to Brunsdon et al. (1998) for the different models feature *p*-values less than 0.001, also indicating that the GWR models deliver better predictions than the corresponding OLS models.

The results obtained by the GWR method provide information about the locally differing estimation coefficients. Therefore, the GWR results do not report a global estimate for each explanatory variable but rather they provide insights into local ranges of the estimates (Minimum, 25% Quartile, Median, 75% Quartile, and Maximum). A complete overview of all GWR model coefficients can be found in the Appendix (Tables A2, A3, and A4).

Besides general tests for spatial autocorrelation reported above, we investigated in particular spatial non-stationarity in the estimates. Table 8 shows some statistics of selected parameter estimates for the models 1A and 1B from both OLS and GWR model specifications. Following former studies (e.g. Fotheringham et al., 2002, p.229; Wang et al., 2005) we compare the ranges of the GWR parameters with a range of ±1 standard deviation and the confidence interval (CI) around the global OLS estimates. Hence, non-stationarity might be apparent if the interquartile (25% and 75% quartile) range of the GWR estimates is greater than a standard deviation range of ±1 of the equivalent OLS estimate (Fotheringham et al., 2002, p.229).

[26] As a rule of thumb, model performance is seriously different if AIC_c values of the models differ at least by a factor of 3 (Fotheringham et al., 2002, p.96).

TABLE 8
Selected parameter estimates for the models 1A and 1B by both OLS (HCSE) and GWR

Method	Statistics	ln *Lot size*	ln *Wind farm*	*Shadowing*	*Distance < 2 km*	ln *Supermarket*	ln *Major road*
OLS	Coefficient	.973	.208	-.098	-.252	-.202	.034
(HCSE)	Std. error	.072	.074	.063	.096	.052	.022
	Lower bound of 95% CI	.926	.069	-.264	-.417	-.275	-.006
	Upper bound of 95% CI	1.020	.348	.067	-.086	-.130	.083
	-1 Std. deviation	.901	.134	-.161	.296	-.254	.017
	+1 Std. deviation	1.045	.282	-.035	1.327	-.150	.061
	Std. deviation range	.144	.148	.126	.192	.104	.044
GWR	Minimum	.713	-.083	-.349	-.297	-.330	-.097
	25% quartile	.820	.066	-.159	-.131	-.254	-.004
	Median	1.041	.123	-.064	-.071	-.218	.057
	75% quartile	1.078	.217	-.017	.276	-.104	.075
	Maximum	1.192	.783	.068	.432	-.017	.155
	Interquartile range	.258	.151	.142	.407	.150	.079

We exemplarily explore spatial non-stationarity in our dataset by providing a selection of variables in Table 8 (models 1A and 1B) and also in Table 9 (model 2), focusing on significant wind-farm-related and other important explanatory variables. The comparison in Table 8 indicates that all GWR interquartile ranges lie outside the standard deviation range of the equivalent OLS estimate, implying that all selected variables are spatially non-stationary. Particularly the interquartile range of ln *Lot size* (.258), *Distance < 2 km* (.407) and ln *Major road* (.079) are beyond the range of the standard deviation of the equivalent OLS parameter (.144, .192 and .044, respectively). In addition, the CI of ln *Lot size* (.926 to 1.020) is within the 25% quartile and the median of the GWR coefficients, indicating that a large share of the local GWR coefficients is higher than the OLS coefficients. Similarly, the CI of *Distance < 2 km* (-.417 to -.086) ranges approximately from the minimum to the median of the local coefficients, indicating that a larger share of these coefficients are higher than the OLS coefficients. Considering the specification of model 2, we can derive similar findings (Table 9). The interquartile range of the GWR coefficients of all selected parameters is greater than the range of ±1 standard deviation of the equivalent OLS estimates. Again, the interquartile range of ln *Lot size* (.135) clearly exceeds the equivalent OLS standard deviation range (.052). Considering the different CI's, we find that the interval of ln *Lake* (.006 to .063) is approximately located around the 75% quartile of the local coefficients, indicating that a larger portion of the local coefficients are smaller than the OLS ones.

TABLE 9
Selected parameter estimates for model 2 by both OLS (HCSE) and GWR

Method	Statistics	ln *Lot size*	*Post-construction*	ln *Major road*	*Street noise*	ln *Lake*
OLS	Coefficient	1.057	-.054	.005	-.063	.034
(HCSE)	Std. error	.026	.035	.014	.020	.016
	Lower bound of 95% CI	1.033	-.121	-.021	-.111	.006
	Upper bound of 95% CI	1.082	.013	.024	-.012	.063
	-1 Std. deviation	1.031	-.089	-.009	-.083	.018
	+1 Std. deviation	1.083	-.019	.019	-.043	.050
	Std. deviation range	.052	.070	.028	.040	.032
GWR	Minimum	.895	-.147	-.021	-.106	-.021
	25% quartile	.964	-.089	-.003	-.088	-.006
	Median	1.062	-.062	.002	-.066	.000
	75% quartile	1.099	-.017	.025	-.046	.038
	Maximum	1.124	.057	.049	.013	.079
	Interquartile range	.135	.072	.028	.042	.044

The spatial distribution of the GWR model coefficients are plotted in Figure 6 (models 1A and 1B) and Figure 7 (model 2). Figure 6 illustrates the spatial distribution for the coefficients of ln *Lot size*, ln *Wind farm*, *Distance < 2 km*, *Shadowing*, ln *Supermarket* and ln *Major road*. The coefficients for ln *Lot size* range from .895 to 1.124 with the median at 1.062. The plot illustrates that coefficient values below 1 are mainly located in the city district of St. Arnold and (north) Mesum. Coefficients larger than unity are predominantly located in Neuenkirchen and Hauenhorst, with the largest values in Hauenhorst, indicating high lot-size sensitivity.

The parameter ln *Wind farm* has its median at .123 with a range of -.083 to .783. The spatial distribution shows the highest values in St. Arnold and Neuenkirchen (> .200), indicating a negative impact on property prices, which appears quite intuitive given the direct proximity to the wind farm site. Furthermore, the spatial pattern of the wind farm distance coefficient reveals a stronger impact on property prices in Neuenkirchen (.200 - .300) than in Hauenhorst and Mesum (< .100) despite approximately similar distances.

The spatial variation of the parameter *Distance < 2 km*, on the contrary, might not be appropriate for capturing the wind farm effects within a two kilometer radius. The map reveals that the largest coefficients are located in St. Arnold and Hauenhorst (.250 - .500) and, therefore, within the two-kilometer radius where negative values were detected based on the findings from model 1A.

The coefficients for the parameter *Shadowing* range from -.349 to .068 with the median at -.064. Negative values can be found particularly in the closest locations to the site, mainly in St. Arnold and Hauenhorst (< -.100), whereas positive values are predominantly located in Neuenkirchen (> -.050). Furthermore, the area of Mesum showed a spatial pattern of increasing coefficient values from the south to the north. Overall, this parameter shows quite reasonable distributions, but should not be overinterpreted due to a significance level of 10%.

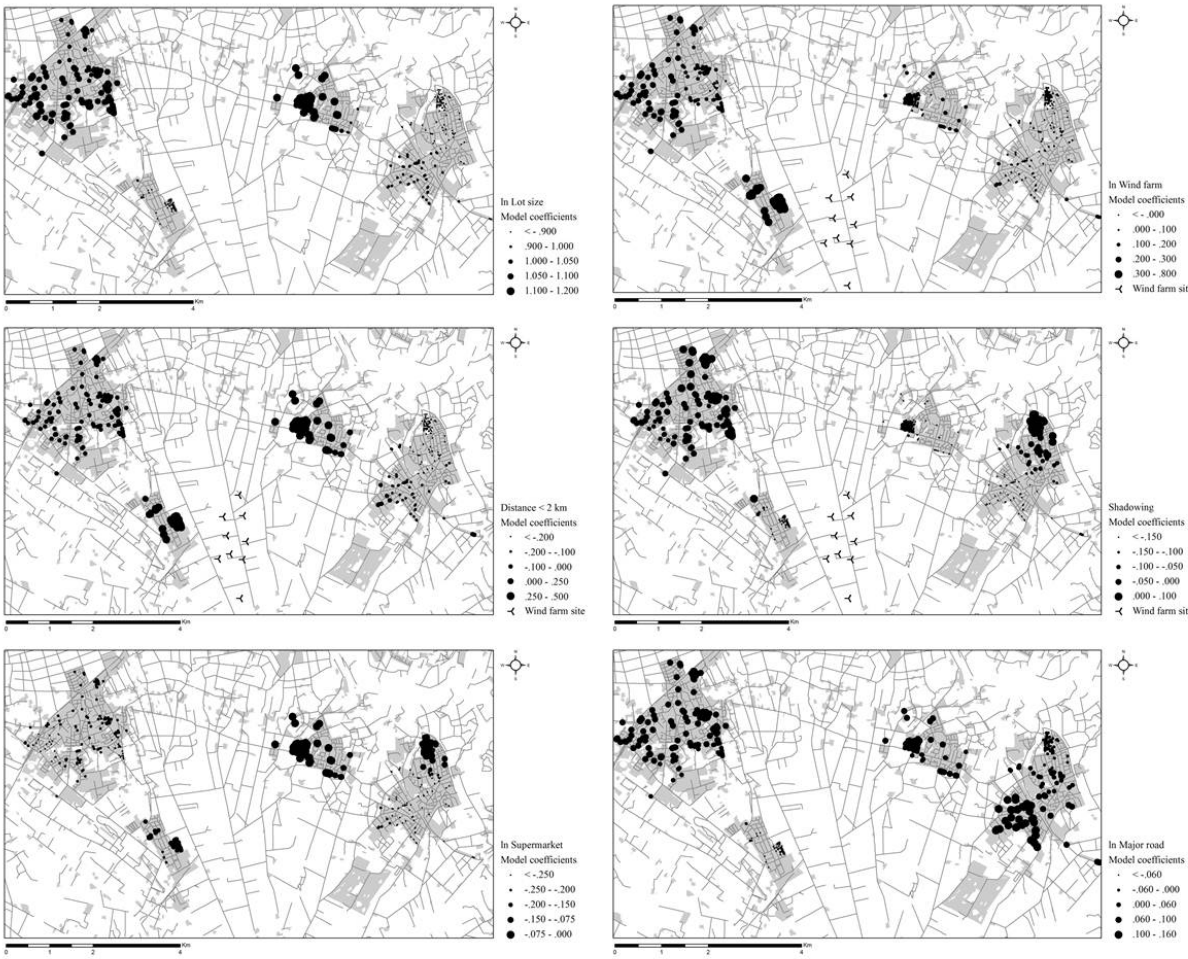

FIGURE 6

Models 1A and 1B - Spatial distribution of selected GWR model coefficients
(parameters for ln *Lot size*, ln *Wind farm*, *Distance < 2 km*, *Shadowing* ln *Supermarket* and ln *Major road*)

The parameter ln *Supermarket* has the median at -.218 with a range of -.330 to -.017. The lowest values are mainly located in the south and middle of Mesum (< -.200). Also Neuenkirchen mainly shows lower values, but some local micro-clusters, which are confined to some streets, are characterized by higher values. The largest values can be found in Hauenhorst (> -.075).

The coefficients for ln *Major road* range from -.097 to .155 with the median at .057. The highest coefficient values can be found in southern parts of Mesum (> .100). Large values are also located in Neuenkirchen and Hauenhorst (> .060). St. Arnold exhibits the lowest coefficient values, basically reflecting the large distance to the next major road (< .000). Also in this case, a significance level of 10% does not permit an overly reliable interpretation.

Figure 7 illustrates different plots of the spatial distribution of selected GWR coefficients of model 2.

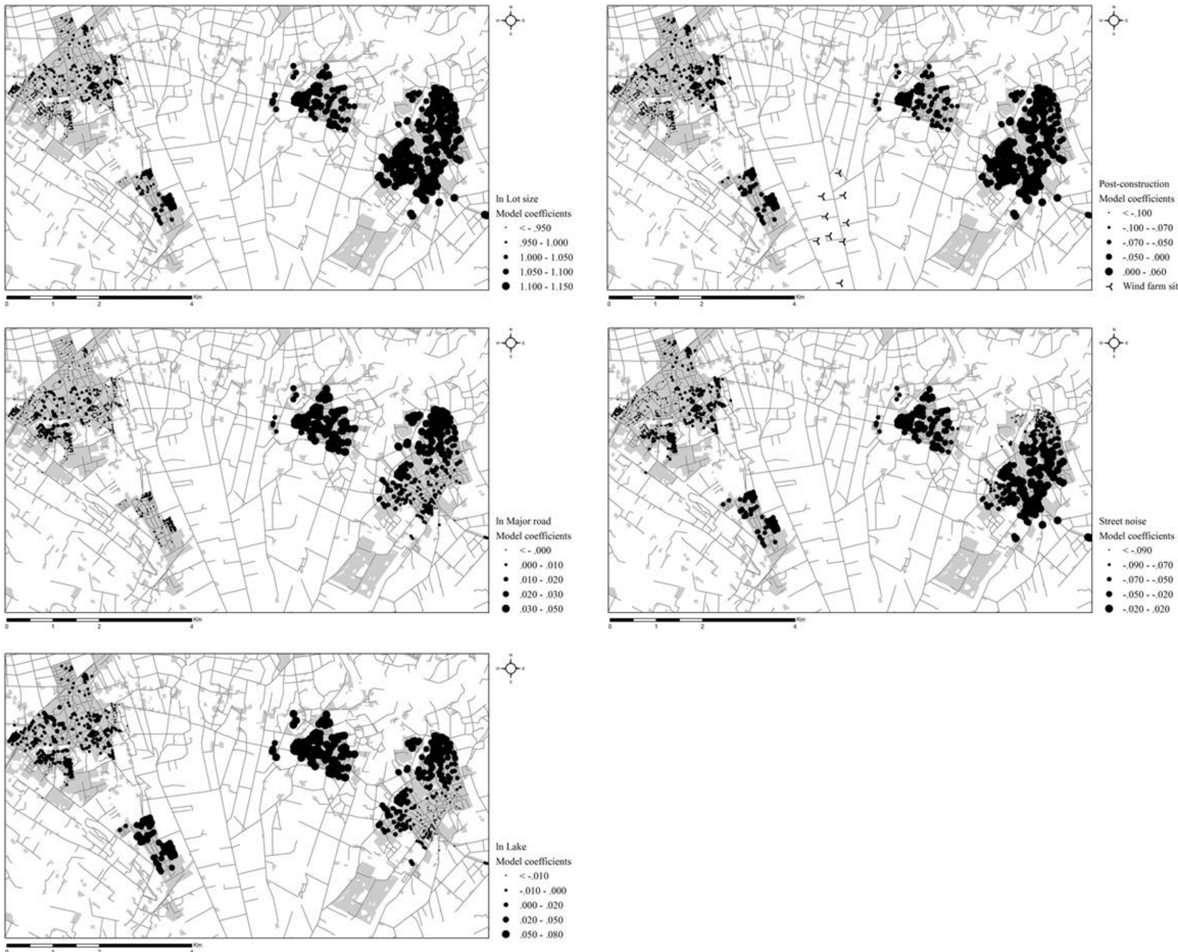

FIGURE 7
Model 2 - Spatial distribution of selected GWR model coefficients
(parameters for ln *Lot size*, *Post-construction*, ln *Major road*, *Street noise* and ln *Lake*)

In the case of model 2, the parameter ln *Lot size* has its median at 1.062 with coefficient ranging from .895 to 1.124. From the plotted map we can see that there is a clear local division between Neuenkirchen and St. Arnold, both with low coefficient values (< 1.050), and Mesum and Hauenhorst, both with high values throughout (> 1.050). Therefore, this provides evidence for higher lot size sensitivity of property prices in Mesum and Hauenhorst.

With the median at -.062 and a coefficient range of -.147 to .057, the spatial distribution of the parameter *Post-construction* largely confirms the findings of the wind farm distance coefficients from model 1A. Negative influences are mainly located in the proximity to the wind farm with larger influence for Neuenkirchen and St. Arnold (< -.050) than for Mesum and Hauenhorst (> -.050). Here, the reliability might again be limited due to a significance level of 10%.

The coefficients for ln *Major road* range from -.021 to .049 with the median at .002. Low coefficient values can be found in Neuenkirchen and St. Arnold (< .010), high values in Hauenhorst (.010 - .050). Mesum shows a spatial pattern of decreasing values from north to south, but with overall higher values than in Neuenkirchen and St. Arnold. In general, the spatial distribution indicates a stronger negative influence of the proximity to a major road in Hauenhorst and Mesum, which might be due to the higher number of major roads in the direct surrounding.

According to the spatial distribution of the parameter *Street noise*, this factor is predominantly influencing property prices in Neuenkirchen and St. Arnold (< -.050). Even positive coefficients are located in Mesum and Hauenhorst. The parameter has its median at -.066, ranging in value from -.106 to .013.

The coefficients for ln *Lake* vary from -.021 to .079 with the median close to 0. Generally, the coefficient values vary across the different districts, with high values in St. Arnold, Hauenhorst and north Mesum (> .020) and mostly lower coefficients in south Mesum and Neuenkirchen (< .000). As the largest lake in this area is located in Neuenkirchen, a positive local influence on property prices in the proximity is found.

V. CONCLUSIONS

In order to investigate the impacts of wind farms on the surrounding area following the current public debates associated with siting processes in Germany, we applied a hedonic pricing model to the property market of the two neighboring cities Rheine and Neuenkirchen in the north of North Rhine-Westphalia. As many hedonic pricing studies only apply standard OLS methods, we compared the model performances of an OLS regression and a GWR. In the framework of the hedonic pricing methodology applied to property market data, a GWR is a useful method in order to explore spatial non-stationarity within the set of variables, and also to improve model performance through the weighting of spatially differing relationships compared to the simplifying estimates of a global OLS model.

According to the global estimation provided by OLS regression, one might be inclined to infer that wind farm proximity has a global, significantly negative impact on the surrounding property prices considered, as is confirmed by the findings from OLS models 1A and 1B, respectively. The application of the GWR revealed a more complex picture of the influencing effects through the weighting of spatial relationships and local variations in the data. Based on local estimates, the GWR revealed negative, wind-farm-related effects that are attributable to strong local influences of the wind farm site. Therefore, predominantly biased by local clustering, global estimations are not appropriate in capturing the impacts of wind farm proximity on property prices. Spatial patterns of the coefficient estimates in our dataset, explored and revealed by applying the GWR, show that the estimates differ substantially across and within the two cities. In addition to that, the GWR also identified spatial micro-clusters, which sometimes encompass either an entire city quarter or else only a few streets.

The GWR findings provide some evidence for negative local effects of proximity to the site and shadowing caused by wind turbines. Nonetheless, further investigation of wind-farm-related impacts focusing on local or even micro-scale effects is needed, particularly to derive general conclusions and reliable recommendations with regard to the impact of wind farm siting in Germany. As social acceptance aspects of the siting of energy facilities become more important, especially with regard to the increasing relevance of decentralized energy supply from renewables, research on external effects of these technologies is crucial.

Furthermore, using data on housing transactions would provide valuable insights on the estimated effects compared to data on property prices, i.e. the price of parcels of land. However, this crucially depends on data availability. Also, applying a repeat-sales analysis (Meese and Wallace, 1997; Heintzelman and Tuttle, 2011) can help to validate the results obtained.

Future research on the impacts of wind farm proximity should essentially include a further investigation of spatial non-stationarity through the application of different statistical testing methods (Leung et al., 2000), for instance using Monte Carlo significance testing in a GWR framework (Wang et al., 2005; Kupfer and Farris, 2007). The exploration of spatial autocorrelation in hedonic pricing models by applying a spatial error and lag model could provide further evidence of the local dimension of the impacts of wind farm sites on house or property values.

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APPENDIX

TABLE A1

Summary statistics – Property sales according to city districts, 1992-2010

	n	Percentage
Hauenhorst	220	100.0
Pre-announcement	98	44.5
Post-announcement	122	55.5
Pre-construction	115	52.3
Post-construction	105	47.7
Sales	197	89.5
Resales	23	10.5
Mesum	470	100.0
Pre-announcement	284	60.4
Post-announcement	186	39.6
Pre-construction	308	65.5
Post-construction	162	34.5
Sales	406	86.4
Resales	64	13.6
Neuenkirchen	556	100.0
Pre-announcement	310	55.8
Post-announcement	246	44.2
Pre-construction	353	63.5
Post-construction	203	36.5
Sales	466	83.8
Resales	90	16.2
St. Arnold	159	100.0
Pre-announcement	74	46.5
Post-announcement	85	53.5
Pre-construction	96	60.4
Post-construction	63	39.6
Sales	133	83.6
Resales	26	16.4

TABLE A2

Model 1A – Statistics of the GWR model coefficients

	Minimum	25% Quartile	Median	75% Quartile	Maximum
Intercept	-18.180	-9.341	-.745	7.149	14.470
ln *Lot size*	.713	.820	1.041	1.078	1.192
Ground value	-.012	.002	.003	.008	.023
Waterfront	.110	.195	.250	.359	.466
ln *Income*	-1.132	-.463	.747	1.210	2.240
Street noise	-.305	-.163	-.064	.001	.140
Visibility	-.126	-.067	-.015	.047	.131
Shadowing	-.349	-.159	-.064	-.017	.068
ln *Wind farm*	-.083	.066	.123	.217	.783
ln *Railroads*	-.106	-.023	.005	.050	.195
ln *Major road*	-.097	-.004	.057	.075	.155
ln *Road*	-.177	-.096	-.081	-.032	.236
ln *CBD*	-.081	-.020	.012	.059	.184
ln *Commercial area*	-.253	-.054	-.012	.051	.238
ln *Supermarket*	-.330	-.254	-.218	-.104	-.017
ln *Transmission line*	-.145	-.066	-.010	.014	.112
ln *1st school*	-.452	-.102	-.008	.039	.185
ln *2nd school*	-.182	-.019	.064	.110	.222

TABLE A3

Model 1B – Statistics of the GWR model coefficients

	Minimum	25% Quartile	Median	75% Quartile	Maximum
Intercept	-18.330	-3.032	-.411	7.609	16.090
ln *Lot size*	.701	.798	1.048	1.082	1.205
Ground value	-.013	.003	.005	.012	.023
Waterfront	.230	.296	.344	.400	.618
ln *Income*	-1.424	-.239	.428	1.067	2.248
Street noise	-.293	-.177	-.063	.002	.159
Visibility	-.161	-.069	-.037	.040	.129
Shadowing	-.435	-.241	-.127	-.080	.042
Distance < 2 km	-.297	-.131	-.071	.276	.432
Distance 2-3 km	-.471	-.384	-.205	-.009	.119
ln *Railroads*	-.105	-.034	-.006	.031	.166
ln *Major road*	-.114	-.002	.045	.065	.155
ln *Road*	-.184	-.100	-.078	-.032	.238
ln *CBD*	-.110	-.048	-.019	.018	.172
ln *Commercial area*	-.251	-.084	-.025	.099	.240
ln *Supermarket*	-.323	-.231	-.200	-.106	.057
ln *Transmission line*	-.148	-.065	-.043	.009	.088
ln *1st school*	-.159	-.083	.007	.056	.181
ln *2nd school*	-.245	-.064	.047	.098	.217

TABLE A4
Model 2 – Statistics of the GWR model coefficients

	Minimum	25% Quartile	Median	75% Quartile	Maximum
Intercept	-22.830	-19.280	-16.850	-15.710	-12.020
ln *Lot size*	.895	.964	1.062	1.099	1.124
Ground value	-.001	.000	.001	.003	.004
Waterfront	.088	.233	.282	.341	.454
Type duplex house	.073	.084	.088	.096	.112
Type untilled parcel	-.199	-.174	-.153	-.145	-.116
ln *Income*	.217	.237	.261	.340	.392
Unemployment	.021	.046	.071	.078	.087
Street noise	-.106	-.088	-.066	-.046	.013
Post-announcement	-.189	-.130	-.099	-.058	.053
Post-construction	-.147	-.089	-.062	-.017	.057
ln *Railroads*	-.070	.039	.053	.071	.141
ln *Major road*	-.021	-.003	.002	.025	.049
ln *Road*	-.090	-.078	-.050	-.041	-.022
ln *Forest*	-.016	.010	.039	.058	.082
ln *Lake*	-.021	-.006	.000	.038	.079
ln *CBD*	-.071	-.042	-.028	-.004	.003
ln *Commercial area*	-.065	-.012	.002	.009	.127
ln *Supermarket*	-.139	-.074	-.043	.004	.031
ln *Transmission line*	-.227	-.130	-.029	.032	.126
ln *1st school*	-.147	-.114	-.027	-.012	.057
ln *2nd school*	-.098	-.064	-.030	-.011	.117

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