The Impact of Wind Farms on Property Values: A Geographically Weighted Hedonic Pricing Model

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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 impacts of wind farms on the surrounding area through property values, by means of a hedonic pricing model using spatial fixed effects and a geographically-weighted regression model. Focusing on proximity and visibility effects caused by wind farm sites, we find that proximity measured by the inverse distance to the nearest wind turbine causes negative impacts on the surrounding property values. Thereby, local statistics reveal varying spatial patterns of the coefficient estimates across and within the city areas and districts. In contrast, no evidence was found for a statistically significant impact of the visibility of the wind farm turbines. The analysis was done for a study area in western Germany.

Keywords: Wind power, Hedonic pricing, Spatial fixed effects, 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).

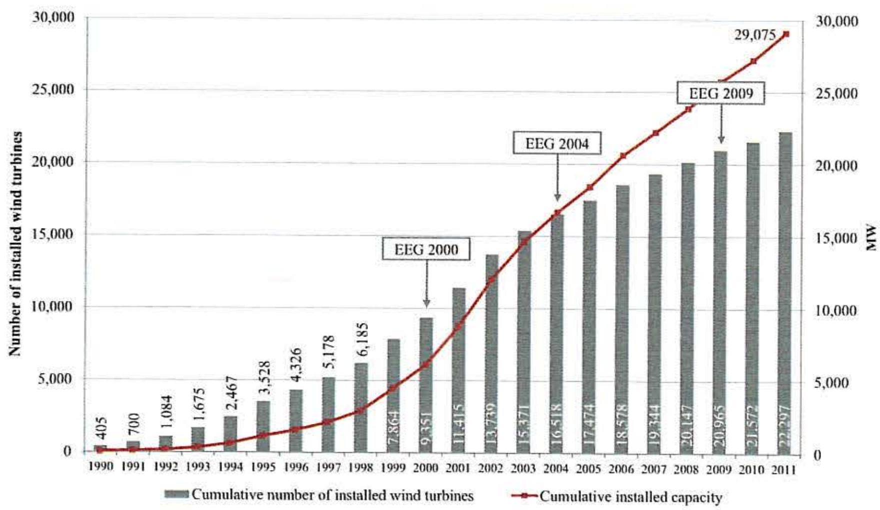

FIGURE 1
Development of the wind energy sector in Germany, 1990-2011
Source: BMU (2012), own illustration

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

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[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.

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 a few analyses in the peer-reviewed literature so far (Sims and Dent, 2007; Sims et al., 2008; Laposa and Mueller, 2010; Heintzelman and Tuttle, 2011; Hoen et al. 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 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.

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[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.

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 accounting for announcement and spatial characteristics of three location groups. The results obtained indicate no significant impact of the planned projects announcement.

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.

In a peer-reviewed and published version of the Hoen et al. (2009) report, Hoen et al. (2011) investigated 7,459 sales of single-family houses surrounding 24 wind farm sites in the United States. They applied various hedonic pricing model specification using spatial fixed effects to account for spatial dependence and spatial autocorrelation. A main focus lay on the impact of view and distance to the site. Overall, they found no statistical significant effects on property sales.

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, 2011)	US (24 sites)	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 hedonic pricing model using spatial fixed effects and a geographically-weighted regression model. The main focus lies on the investigation of site proximity and visual impacts of wind farms, such as the impact of visibility and shadowing, as these are most often the central subject of public debates associated with siting processes. Therefore, in a first step, we apply three different spatial fixed effects models in order to capture effects of unobserved spatially-related factors.[6] As spatial fixed effect models have been applied to the case of wind farm effects (e.g. Heintzelman and Tuttle, 2011 and Hoen et al., 2009, 2011), we improve upon the already applied methodologies in the literature investigating the importance of the view on the facility by means of a fixed viewshed effect model specification. Controlling for visibility effects will emphasize and highlight the importance of distance to the facility. In this context, the application of Geographical Information System (GIS) techniques[7] allow for an accurately derivation of viewsheds[8] in a 3D environment on basis of high resolution geodata.

In a second step, we additionally apply a Geographically Weighted Regression (GWR) analysis in order to gain a more detailed picture of local impacts and spatially varying relationships compared to global estimation results. This particularly includes the consideration of spatial correlation and the analysis of the biasing influence of spatial non-stationarity on the estimation results. To our knowledge, there is no hedonic pricing analysis applied to wind farm impacts that specifically adopted a GWR approach or specifically 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.

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. To our knowledge, there is also no scientific study on wind farm impacts using German real estate market data. 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 the different model specifications. Section 5 concludes and also 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

[6] The three spatial fixed effect model specifications are varying according to their geographical scale, where smaller scales of the fixed effects allow for tighter control with regard to omitted variable bias (Heintzelman and Tuttle, 2011). The spatial fixed effects included in our analysis are fixed city effects, fixed city district effects and fixed cadastral district effects. For a detailed description of the model specifications, see section 3.

[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 considered properties). The visibility of a large-scale wind farm in the close vicinity of a property might have a significant impact on its value.

(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 (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

Estimation methods

An attempt to estimate the impacts of wind farm proximity in the framework of a hedonic pricing study has to take into account the possible bias caused by model misspecification, particularly through omitted variables. In this context, the main concern refers to regional or local factors which remain unobserved. In case of unobserved factors, partly explaining the variation in property prices or being correlated with included variables, the model estimations will likely be biased and, therefore, unreliable (Chay and Greenstone, 2005; Greenstone and Gayer, 2009; Kuminoff et al., 2010).

The unobserved variables bias can directly be addressed applying a spatial fixed effects model specification. Spatial fixed effects basically capture spatially clustered unobserved influences in the considered study area through incorporating a set of dummy variables, e.g. representing city districts of the study area. According to this example, the fixed city district effect will then implicitly absorb all unobserved factors within the defined geographical scale of this fixed effect. However, the effect of this approach in capturing spatially clustered unobserved factors crucially depends on the definition of the geographical scale. The definition of the geographical scale is accompanied by a tradeoff between the level of control and the variation in the explanatory variables (Heintzelman and Tuttle, 2011). Therefore, a higher level of control for omitted variables, i.e. a small geographical scale of the fixed effect, results in less variation in the explanatory variables due to the limited scope of the fixed effect (Heintzelman and Tuttle, 2011). The definition of several scales for spatial fixed effects in different model specifications might seem reasonable in order to derive a comprehensive picture of the ability of spatial fixed effects in capturing spatially clustered unobserved factors.

Accompanied by spatially clustered omitted variables, we have to be aware of spatial dependence and spatial heterogeneity. Spatial dependence refers to dependencies among spatially contiguous observations within the dataset which cause spatial autocorrelation (Anselin and Getis, 2010). Thus, based on Tobler's First Law of Geography, spatially nearby observations are stronger correlated to each other than observations farther away (Tobler, 1970). Likewise, unobserved factors for one observation may be correlated to unobserved factors for a neighboring observation, inevitably causing spatial autocorrelation. Therefore, not controlling for spatial autocorrelation would bias our estimations. We address this spatial dependence problem applying spatial fixed effects and error clustering in a procedure proposed by Heintzelman and Tuttle (2011). According to this, using spatial fixed effects is methodologically related to the application of a spatial lag model, where the spatially weighted average of neighboring observations in the spatial lag model is given here by the scale of the fixed effects. Similarly, the error clustering is related to employing a spatial error model allowing for correlation of error terms.[9] Besides the wide application of spatial econometric techniques, such as the spatial lag and spatial error model, "spatial fixed are clearly the preferable strategy for addressing spatially correlated omitted variables in cross-section data" (Kuminoff et al., 2010, p.158), as spatial fixed effects offer a less rigid and more flexible structure on spatial relationships between included and omitted variables (Kuminoff et al., 2010).

The hedonic pricing model in a spatial fixed effects and error clustering specification is given by:

$$\ln p_{ijt} = \alpha_j + \lambda_t + W_{ijt}\beta + S_{ijt}\gamma + N_{ijt}\delta + \eta_{jt} + \varepsilon_{ijt}, \qquad [1]$$

[9] For details on the spatial lag and error model, see Anselin (1988).

where p_{ijt} is the sales price of property i in group j at time t, α_j represents the spatial fixed effect, λ_t denotes the set of time dummy variables (month and year), W_{ijt} represents the wind farm related variables, S_{ijt} describes a set of structural variables, N_{ijt} denotes the neighborhood variables, η_{jt} and ε_{ijt} are grouped and individual-level error terms, and β, γ as well as δ are the parameters to be estimated.[10]

We use three different spatial fixed effect specifications which are derived according to the administratively defined structure of the study area. The study area contains two cities which again consist of four defined city districts and 39 cadastral districts, respectively.[11] From large to small geographical scale, the first three group the observations with regard to their location in one of the cities (2 groups), in one of the city districts (4 groups) and in one of the cadastral districts (39 groups). In a fourth specification, the fixed viewshed effects, we group the observations according to the number of visible turbines (10 groups). Compared to three specifications described above, the fixed viewshed effects are not deduced from administrational structure, rather from an underlying spatial structure. The fixed viewshed effects should essentially absorb the influence of wind farm visibility on properties, therefore, highlighting the importance of pure proximity in the sense of distance measures. In many hedonic pricing studies focusing on wind farm impacts, simple distance measures are used as a proxy for various effects that is caused by proximity to the facility. But besides the measurement of distance, proximity can also be investigated in the sense of visibility, shadowing effects and aural impacts. Therefore, applying the fixed viewshed effect specification, we try to provide a more differentiated picture on potential impacts caused by wind farms presence.

Spatial heterogeneity is a further concern that we should be aware of. Spatial heterogeneity refers to the presence of spatial non-stationarity within the dataset, as the measurement of a relationship depends on where the measurement is taken (Fotheringham et al., 2002, p.9). There might be various dependencies between spatially nearby observations, so that spatial relationships may vary across the considered study area. We address a form of spatial heterogeneity, again, using spatial fixed effects. Furthermore, we explore spatial heterogeneity in our dataset by means of a GWR, as this approach allows for a comprehensive view on spatial relations providing local statistics.

Most importantly, compared to conventional regression models, the GWR provides separate, local regressions for each observation, instead of generating a single, global regression. Therefore, it is possible to account for different local relationships, weighting each observation adaptively.

According to this, the GWR model specification is given by:

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[10] We apply a semi-log specification with
$W = \{w', \ln w''\}$, where w' (w'') does not enter (does enter) the regression in the log scale;
$S = \{s', \ln s''\}$, where s' (s'') does not enter (does enter) the regression in the log scale;
$N = \{n', \ln n''\}$, where n' (n'') does not enter (does enter) the regression in the log scale.
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).

[11] A more detailed description on the study area is provided in the data subsection.

$$\ln p_{it} = W_{it}\beta(u_i, v_i) + S_{it}\gamma(u_i, v_i) + N_{it}\delta(u_i, v_i) + \varepsilon_{it}, \qquad [2]$$

where (u_i,v_i) indicates the coordinates of the ith observation. Again, following 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 ($\beta(u_i,v_i)$, $\gamma(u_i,v_i)$, $\delta(u_i,v_i)$) 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 2 graphically illustrates a spatial kernel and a GWR with adaptive spatial kernels.

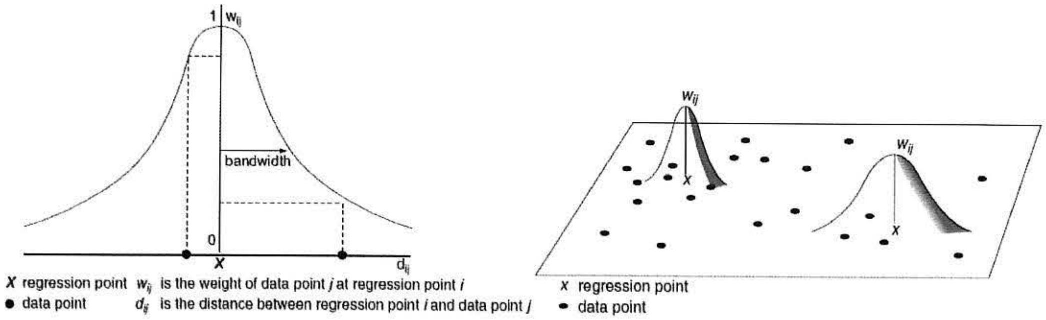

FIGURE 2
A spatial kernel and a GWR with adaptive spatial kernels
Source: Fotheringham et al. (2002, pp.44 and 47)

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 2).

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.[12] Following Fotheringham et al. (2002, p.58), that is,

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

[12] We are aware that the appropriability of the Nth nearest neighbor weighting is an empirical matter, as this is a nonparametric approach, forcing each observation to have the same number of neighbors (Anselin, 2002). However, accounting for spatial variations in the framework of a GWR, the Nth nearest neighbor weights provide a straightforward method capturing the 'bump of influence' around i, without assuming that the given administrational structure of the study area (e.g. through cadastral districts) is representing local variations appropriately. There is vast body of literature on the specification of the weight matrices in spatial analysis. For a detailed discussion on the construction of weights, see Smirnov and Anselin (2001) and Anselin (2002).

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).

In summary, we address spatial autocorrelation caused by spatially clustered unobserved factors and spatial heterogeneity in the sense of spatial non-stationarity using various spatial fixed effect model specifications. Additionally, we emphasize the relevance of spatial heterogeneity through the application of a GWR. We explicitly explore the importance of locally varying relationships, exposing additional insights that can be derived from local statistics compared to global regressions.

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 city 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.[13] In 2011, a population of 26,900 lived within a radius of about 5.5 kilometers around the site.

As Figure 3 illustrates, the considered study area contains two cities (the city of Rheine and the city of Neuenkirchen), each consisting of two city districts. City districts of Rheine are Mesum and Hauenhorst, and Neuenkirchen (city area) and St. Arnold in the case of Neuenkirchen. Besides the apparent spatial structure depicted in Figure 3, the German land register provides further spatial classifications. In the German land register, cadastral districts are the smallest spatial unit that groups a particular number of parcels in respect of their location. According to the cadastral register of the region, each property, i.e. each parcel, is assigned to a particular cadastral district. The property sales in our dataset can be grouped correspondent to 39 cadastral districts. As described in the estimation methods subsection, the different spatial administrative structures defined, are used to incorporate spatial fixed effects in our hedonic pricing model.

In 2000, the local 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 3 illustrates the study area and the location of the wind farm site.

[13] 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. 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. 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.

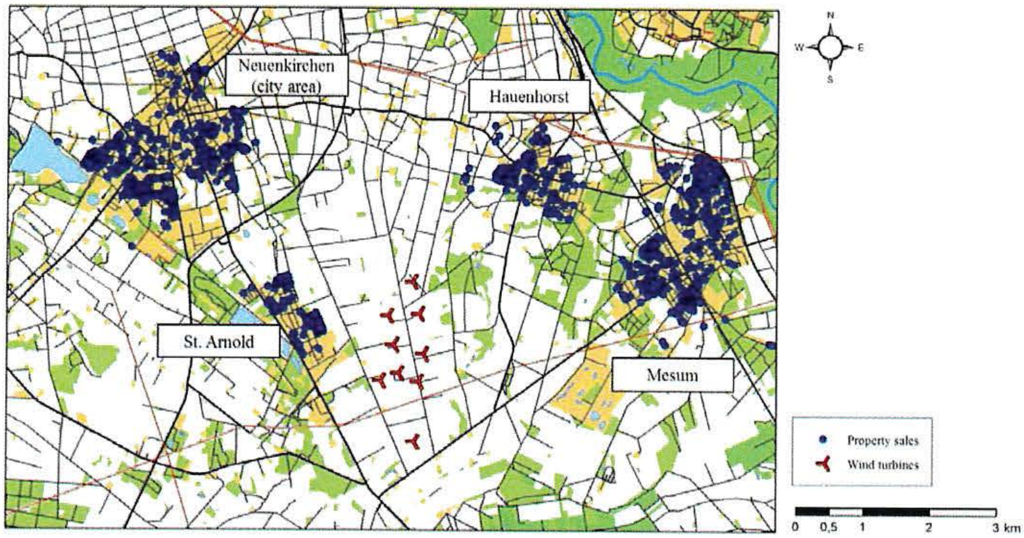

FIGURE 3
Study area
Source: Own illustration, based on data provided by the Geodatenzentrum NRW (2011)

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[14] 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)[15]. 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 cities, city districts, wind farm announcement and construction.[16]

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.[17] 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.[18] Furthermore, in our study, we only consider developed and undeveloped properties

[14] Rheine and Neuenkirchen are cities that both belong to the federal district of Steinfurt. In this context, the term 'federal district' is equivalent to a 'county council'.

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

[16] Re-sales were not excluded from the data sample as these only account for a small share of the total sales. As a consequence, the re-sales data does not allow provide a sufficient basis for applying a repeat sales analysis.

[17] The data provided by the Expert Advisory Boards only contained the separated price for the property in terms of a parcel of land.

[18] Hedonic pricing studies using house prices include a large set of 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. For parcels of land, structural variables can be limited to the lot size and the development status, whereas more emphasis has to be put on neighborhood variables, capturing locational attributes.

for residential utilization only.[19] The regional land use, such as residential utilization, is defined in the regional development plan.

TABLE 2
Summary statistics – Property sales in the study area, 1992-2010

	N	Percentage
Total no. of observations	1,405	100.0
City of Rheine	690	49.1
City district Hauenhorst	220	15.7
City district Mesum	470	33.4
City of Neuenkirchen	715	50.9
City district Neuenkirchen (city area)	556	39.6
City district St. Arnold	159	11.3
Total sales	1,202	85.6
Total re-sales	203	14.4
Pre-announcement	766	54.5
Post-announcement	639	45.5
Pre-construction	872	62.1
Post-construction	533	37.9

Table 3 provides summary statistics of the 15 wind farm related variables and the other 17 explanatory variables that were tested in different model specifications in order to explain the variation in the property prices.

The set of wind farm related variables tries to measure the wind farm presence in different ways. First of all, the set includes Euclidean distance measurements as the most commonly used proxies of wind farm effects.[20] We used the inverse distance from each property to the nearest wind turbine which also allowed for the consideration of the date of construction.[21] Besides the inverse distance measure from each property to the wind farm, we also tried to identify local distance effects within five kilometers around the wind farm, using dummy variables containing properties in 0.5 km steps.

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 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 temporary presence of shadowing effects for each property during the year.[22] In this context, we tested a simple dummy variable as well as a variable taking into account shadowing caused by multiple turbines.

[19] In comparison to an untilled parcel, we include four types of possible development statuses: a parcel with a single-family house, a parcel with a duplex house, a parcel with a row house and a parcel with a multi-family house.

[20] All distance variables, also these that were used to capture general neighborhood features, were calculated using GIS software. 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.

[21] Using inverse distance measures to the nearest turbine, the measured values increase with decreasing distance. Values for property sales with sales dates before the turbines existence measure the inverse distance to the next existing wind farm in neighboring regions at that time.

[22] We consider properties as impacted by shadowing effects, if these are located in the affected areas.

TABLE 3
Descriptive statistics

	Variable	Units	Mean	Std. dev.	Min	Max
Wind farm related	ln (*Inverse Wind farm distance*)	ln *m*	-9.26	0.99	-8.57	-6.89
	Distance 0.5 - 1 km	dummy	0.00	0.06	0	1
	Distance 1 - 1.5 km	dummy	0.03	0.18	0	1
	Distance 1.5 - 2 km	dummy	0.01	0.11	0	1
	Distance 2 - 2.5 km	dummy	0.06	0.24	0	1
	Distance 2.5 - 3 km	dummy	0.01	0.11	0	1
	Distance 3 - 3.5 km	dummy	0.04	0.20	0	1
	Distance 3.5 - 4 km	dummy	0.09	0.28	0	1
	Distance 4 - 4.5 km	dummy	0.04	0.19	0	1
	Distance 4.5 - 5 km	dummy	0.09	0.28	0	1
	Shadowing	dummy	0.03	0.18	0	1
	Shadowing (No. of turbines)	classes	0.08	0.47	0	3
	Visibility (No. of visible turbines)	classes	0.29	0.99	0	9
	Announcement effect	dummy	0.45	0.50	0	1
	Construction effect	dummy	0.38	0.49	0	1
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
	Waterfront	dummy	0.00	0.07	0	1
	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
Neighborhood/ Spatial	ln *CBD*	ln *m*	-6.83	1.12	-8.28	2.30
	ln *Supermarket*	ln *m*	-6.28	0.60	-7.45	-2.52
	ln *Commercial area*	ln *m*	-7.36	0.88	-8.56	-3.71
	ln *School*	ln *m*	-6.41	0.60	-8.01	-4.25
	ln *Forestland*	ln *m*	-5.29	0.90	-6.54	2.30
	ln *Major road*	ln *m*	-5.25	0.89	-6.72	-2.11
	ln *Road*	ln *m*	-2.48	0.42	-4.53	-0.02
	Street noise	classes	1.07	0.38	1	5
	ln *Railroads*	ln *m*	-7.53	1.28	-8.91	-3.54
	ln T*ransmission line*	ln *m*	-6.85	0.74	-7.72	-3.47
	ln *Lake*	ln *m*	-6.40	0.73	-7.52	-3.23

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[23] with an

[23] 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. We are aware of the suggested potential inaccuracies using predicted viewshed in the GIS-literature (Maloy and Dean, 2001; Riggs and Dean, 2007). There is tradeoff regarding the effort of conduction systematic field visits for a whole region, which would surely guarantee for an accurate definition of visibility, and the use of GIS techniques, which dependent on the data resolution that might produce inaccuracies. However, we do believe that in our case, an appropriate degree of accuracy of the viewshed calculations is ensured, given the precision of the obtained digital surface model. The digital surface model used, recorded elevations every single meter and is,

accuracy of one meter, which was provided by the Geodatenzentrum NRW.[24] 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 4 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.[25] The calculated viewsheds were used to specify the fixed viewshed effect model, described in the estimation methods subsection.

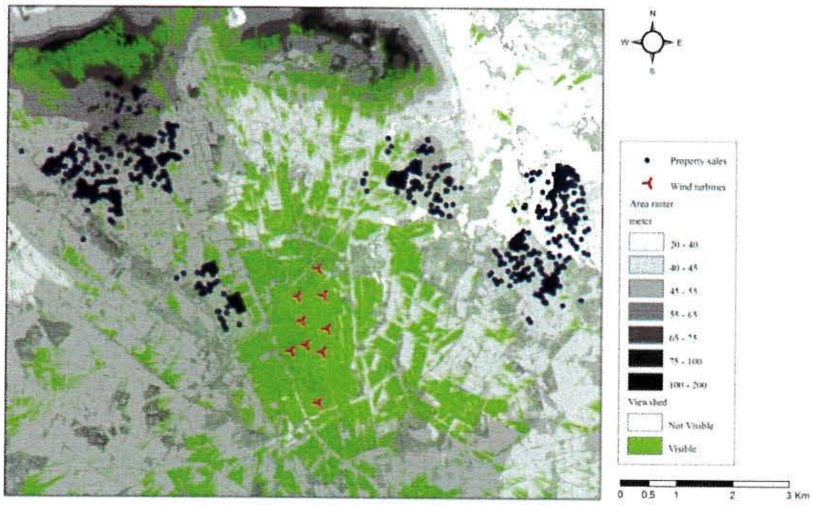

FIGURE 4
Visibility analysis
Source: Own calculation and illustration, based on data provided by the Geodatenzentrum NRW (2011)

The dummy variables capturing possible effect of project announcement and construction base on the date of the wind farm project announcement (June 2000) and date of the wind farm construction (August 2002).

Substantial 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[26] 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.

The structural variables, such as the sales price, the lot size, and the four types of development statuses of the properties, were directly taken from the property sales dataset provided by the Expert Advisory Board. We investigated the impact of different development statues compared to an undeveloped, untilled, parcel. The waterfront variable was derived using data services of the Topographic Information Management of the federal state of North

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therefore, more precise compared to the digital terrain models investigated and reviewed in the GIS literature mentioned.

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

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

[26] 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).

Rhine-Westphalia (Topographisches Informationsmanagement NRW).[27] Most importantly, we expect a highly positive relationship between the property price and the lot size.

The spatial variables characterizing the neighborhood for each property also predominately contain Euclidean distance measures to the amenities and disamenities in the surrounding area, e.g. shopping opportunities or proximity to the road network. Data on the neighborhood features and their location was obtained from statistical offices on the state, district, and city level.[28] Commonly used data on neighborhood variables, such as crime rates, unemployment or income distribution was only available at the city district level or even city level. As these variables only vary over time and the four different city districts (or two cites), effects are implicitly captures by the spatial fixed effects and time dummies.

IV. RESULTS

In this section, we firstly discuss the results obtained from the different spatial fixed effects model specifications, focusing on the wind farm related variables. Secondly, we further investigate wind farm proximity and visibility in a GWR model.

Spatial fixed effects

Table 4 provides an overview of the estimation results obtained from applying different spatial fixed effects specifications.

According to the overall model performance, we find that all four spatial fixed effects specifications performed very well with regard to the adjusted R^2 obtained.[29] The specification with the tightest controls for spatially clustered omitted variables, the fixed cadastral district specification, performed best. Overall, we obtained mostly consistent results across all specifications regarding the expected signs.

We use a stepwise procedure of introducing the wind farm related variables in order to prevent multicollinearity, particularly in case of the different distance measures.

Regarding the wind farm related variables, most importantly, the inverse distance to the nearest turbine is negatively significant across all models. Therefore, a 1% increase in the inverse distance (i.e. a decrease of distance to the nearest turbine) decreases the property sales price by -.047% to -.098%.[30] Taking into account the different geographical scales of the fixed effects, tighter controls lead to less significance and lower coefficients, confirming the mentioned tradeoff between control for omitted variables and variation. The fixed viewshed effect model revealed the highest coefficient (-.098 at 1% significance level) for the inverse distance variable. Therefore, controlling for visibility effects underlined the importance of proximity measured by simple distance.

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

[28] 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.

[29] We tested for autocorrelation, multicollinearity and heteroskedasticity applying the Durbin-Watson test, variance inflation factor (VIF) and the White test, respectively, and corrected if necessary.

[30] For an average property price of about 42,500€, the estimated coefficients correspond to a decrease of 19.98€ to 41.65€ for a 1% decrease of distance to the nearest turbine.

TABLE 4
Estimation results for the different spatial fixed effects specifications

Variable ‡	Fixed City Effects coef (SE)		Fixed City District Effects coef (SE)		Fixed Cadastral District Effects coef (SE)		Fixed Viewshed Effects coef (SE)	
ln (*Inverse wind farm distance*)	-.067***	(.024)	-.053**	(.043)	-.047**	(.022)	-.098***	(.042)
Distance 0.5 - 1 km	-.287**	(.139)	-.215*	(.152)	-.297**	(.148)	-.286*	(.303)
Distance 1 - 1.5 km	-.153*	(.101)	-.079	(.105)	-.175*	(.102)	-.180	(.291)
Distance 1.5 - 2 km	-.107	(.111)	-.044	(.141)	-.115	(.131)	-.108	(.290)
Distance 2 - 2.5 km	-.080	(.091)	-.118	(.106)	-.116	(.072)	.031	(.285)
Distance 2.5 - 3 km	-.178	(.216)	-.218	(.119)	-.300	(.199)	-.110	(.370)
Distance 3 - 3.5 km	-.176	(.123)	-.194*	(.109)	-.195	(.133)	-.128	(.290)
Distance 3.5 - 4 km	-.114	(.109)	-.139	(.107)	-.155	(.147)	-.098	(.273)
Distance 4 - 4.5 km	.011	(.115)	-.000	(.115)	-.142	(.124)	.035	(.321)
Distance 4.5 - 5 km	.009	(.114)	.006	(.123)	-.108	(.143)	.051	(.308)
Shadowing	-.091**	(.043)	-.022	(.054)	-.058	(.047)	-.157***	(.039)
Shadowing (No. of turbines)	-.034**	(.016)	-.001	(.019)	-.023	(.017)	-.054***	(.014)
Announcement effect	-.032	(.103)	-.039	(.087)	.044	(.097)	-.077*	(.042)
Construction effect	-.102	(.068)	-.108***	(.039)	-.119*	(.068)	-.028	(.039)
ln *Lotsize*	1.069***	(.037)	1.069***	(.033)	1.082***	(.030)	1.063***	(.027)
Waterfront	.076	(.280)	.005	(.286)	.026	(.313)	.051	(.341)
Type single-family house	.183***	(.054)	.175***	(.022)	.138***	(.068)	.180***	(.079)
Type duplex house	.293***	(.058)	.282***	(.027)	.235***	(.073)	.291***	(.082)
Type row house	.270**	(.106)	.241**	(.057)	.164**	(.093)	.222**	(.079)
Type multi-family house	.326***	(.077)	.311***	(.056)	.295***	(.098)	.343***	(.069)
ln *CBD*	.049***	(.036)	.048***	(.043)	.029**	(.030)	.030***	(.023)
ln *Supermarket*	.058***	(.051)	.053***	(.050)	.027	(.057)	.077***	(.042)
ln *Commercial area*	.067***	(.038)	-.035*	(.025)	.017	(.057)	.029*	(.023)
ln *School*	.016	(.025)	.024	(.030)	-.019	(.038)	-.004	(.035)
ln *Forestland*	-.021**	(.020)	-.022**	(.032)	-.019	(.032)	-.014	(.022)
ln *Major road*	-.026**	(.027)	-.024**	(.025)	-.031**	(.030)	.005	(.010)
ln *Road*	.099***	(.048)	.102***	(.038)	.090***	(.040)	.109**	(.048)
Street noise	-.022	(.023)	-.031*	(.017)	-.013	(.026)	-.036*	(.022)
ln *Railroads*	-.056***	(.043)	-.029*	(.042)	.007	(.074)	.017	(.024)
ln *Transmission line*	-.014	(.013)	-.001	(.035)	.024	(.085)	.012	(.024)
ln *Lake*	-.023*	(.024)	-.006	(.024)	-.027	(.044)	-.027*	(.025)
(Intercept)	2.891***	(.717)	3.551***	(.991)	2.986**	(1.397)	3.293***	(.779)
Number of observations	1,405		1,405		1,405		1,405	
Adjusted R^2	0.889-0.890		0.890-0.892		0.903-0.904		0.886-0.888	
AIC_c	458.5-469.8		440.3-454.4		311.5-318.5		495.7-517.2	
Time dummies (year and month)	Yes		Yes		Yes		Yes	
Clustered errors	Yes		Yes		Yes		Yes	

*, ** and *** indicates significance at the 10%, 5% and 1% levels respectively.
‡ Following the regression procedure of Heintzelman and Tuttle (2011), the wind farm related variables (ln (*Inverse Wind farm distance*), *Shadowing*, *Shadowing (No. of turbines)*, *Announcement effect* and *Construction effect*) were included individually to the set of structural, neighborhood and spatial variables. The set of the nine distance variables were included jointly. Because of high consistency in the estimates for the structural, neighborhood and spatial variables, we have taken the coefficients from the ln (*Inverse Wind farm distance*) regression representatively. In the bottom part of the table we present the ranges for the adjusted R^2 and the AIC_c, respectively.

Further, investigating distance to the wind farm site through a set of dummy variables, negative wind farm impacts are mostly detectable in the close vicinity within the first 1.5 km around the site. Hence, within the first kilometer around the wind farm, prices decreased by 21.5% to 29.7% according to the estimations. In case of the fixed cadastral district model, the estimate of -29.7% is even significant at the 5% level. For a distance of 1 km to 1.5 km, the negative impact decreases and is only significant at the 10% level in case of the fixed city effect and fixed cadastral effect model (-15.3 and -17.5, respectively). The negative impact within 3 and 3.5 km in the fixed city district effects model seems quite ambiguous, but is more or less negligible with a 10% significance level only.

According to the shadowing variables, the estimated results hardly allow a clear interpretation. The coefficients of the shadowing dummy are quite diverse across the different spatial fixed effects models, ranging from -.022 to -.157. Furthermore, the estimates only became significant in the fixed city effects (at the 5% level) and fixed viewshed effects model (at the 1% level), respectively. As the measurable effects of shadowing are only limited to parts of one city district (St. Arnold) and, therefore, only to a small number of observations, this variable might not be adequate in representing a potential effect caused by shadowing. A further explanation, also regarding the highly negative coefficient in the fixed viewshed effects model, might be that in essence the shadowing dummy is quite similar to a small scale distance dummy. The same argumentation applies to second shadowing variable.

Regarding a possible effect of announcing the wind farm project, no significance was found in the fixed city effects, fixed city district effects and fixed cadastral district effects model specifications. Despite a small negative effect (-.077%) at the 10% level in the fixed viewshed effects model, the impact of announcing the project remains highly doubtful.

The construction of the wind farm negatively impacted property sales in the two overall best performing model specifications, with significance levels of 1% (fixed city district effects) and 10% (fixed cadastral effects). Thus, properties that were sold after the construction of the wind farm showed price decreases between 10.8% and 11.9%. Despite the different significance levels, there is evidence for a negative construction effect, particularly as we used time dummies for years and month to capture annual and seasonal variations.

The other explanatory variables mostly also perform well in the sense of an intuitive interpretation. As expected, the lot size of a property is the most important determinant of its sales price, with estimated coefficients of 1.062 to 1.082. Therefore, a 1% increase in the lot size of a property increases its value about approximately 1%. Positively related to the property prices is also the development status compared to an undeveloped or untilled parcel.

The proximity to the city center (variable ln *CBD*) and supermarkets is also positively significant across nearly all models. This goes along with the common circumstance that properties in the city center have higher values than properties in remote areas. Furthermore, the proximity to forestland was found to be negatively correlated to property values, with significance at the 5% level in the case of the fixed city effects and fixed city district effects specification. In this case the forestland variable cannot be in interpreted as an indicator for an environmental amenity but rather representing less centrality of the location.

Major roads in the close vicinity of properties have significant negative impacts on their values, whereas the proximity to roads is positively significant across all models. While the proximity to a major road implies negative effects of high traffic density (ln *Major road*), the proximity to the cities road network indicates positive effects, such as a higher degree of accessibility (ln *Road*).

The proximity to railroads, which is also frequently investigated by means of hedonic pricing studies (Bowes and Ihlanfeldt, 2001; Theebe, 2004), only appeared negative significant in the fixed city effects and city district effects models (at 1% and 10% level, respectively). Using fixed cadastral district and fixed viewshed effects, the railroads variable turned out to be insignificant and changed signs as well. In this case, the results obtained barely allow for a clear interpretation.

No statistical evidence was found for the impact of proximity to schools, transmission lines, lakes as well as for higher street noise or the availability of a waterfront.

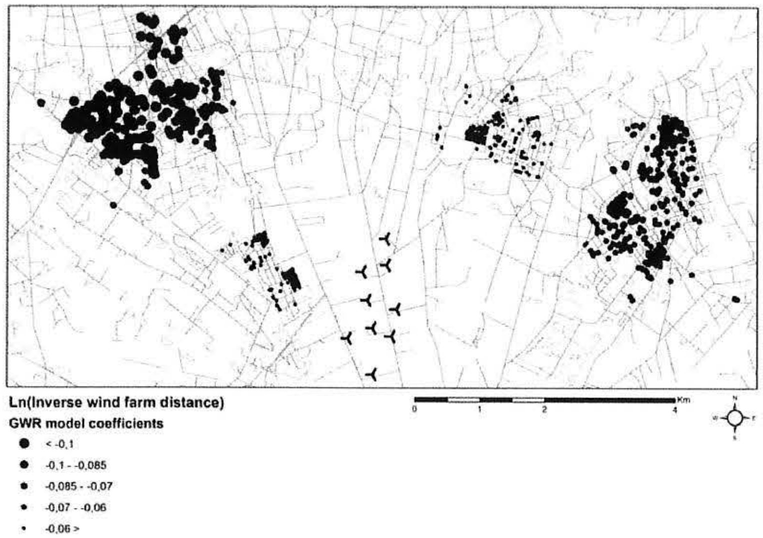
Geographically weighted regression

In a similar model setup, compared to specifications described in the last subsection, specifically regarding the composition of the included variables, we applied a GWR model to estimate local coefficients and significance levels for the variables ln (*Inverse wind farm distance*) and *Visibility (No. of visible turbines)*. The inverse distance to the wind farm is analyzed in a local GWR model in order to reveal a more complex picture of the local variation of the estimates and significance. The information provided by the variable *Visibility (No. of visible turbines)* was used to specify the fixed viewshed effects model in the previous subsection. Therefore, this variable is analyzed in a GWR model in order to assess the local distribution of possible visibility effects and to derive more insights about the predictive performance of a fixed viewshed model. Statistics on the GWR coefficient estimates for both model specifications are provided in the Appendix (Tables A1 and A2).

Both local model specifications performed very well in respect of the given quasi-global adjusted R^2 (.910 for both variables) and AIC_c (308.1 for the distance variable and 312.5 for the visibility variable). Therefore, comparing the model performance of the local GWR and the global spatial fixed effects specifications on the basis of the two indicators, the local model exhibits a similar performance power like the fixed cadastral effects model. Figures 5 and 6 map the local coefficient estimates and significance levels for the investigated variables.

According to Figure 5(a), that provides an overview of GWR model coefficients for Ln (*Inverse wind farm distance*), we can identify strong spatial variation within the study area. The strongest impacts are located predominantly in Neuenkirchen (city area) and not, as expected, in areas which are in the immediate vicinity of the wind farm site. Now also taking into account the local variation of the significance levels (Figure 5(b)), there is a clear difference between properties located in the west and the east of the study area. In the east of the study area, particularly in Mesum, the inverse distance variable mainly becomes significant only at the 10% level or even not significant at all. On the contrary, properties located in the west, especially in Neuenkirchen (city area) and St. Arnold, are negatively influenced with significance levels at 1% and 5%, respectively. Properties in the immediate vicinity of the wind farm (St. Arnold and Hauenhorst) are also negatively significant affected (mainly at the 5% level). In the city district Neuenkirchen (city area), we can identify the strongest significance, whereas the significance decreases towards the city center. Overall, the local estimations for the inverse distance to the wind farm provide evidence for a stronger negative impact on the city of Neuenkirchen than on the city of Rheine.

(a)



(b)

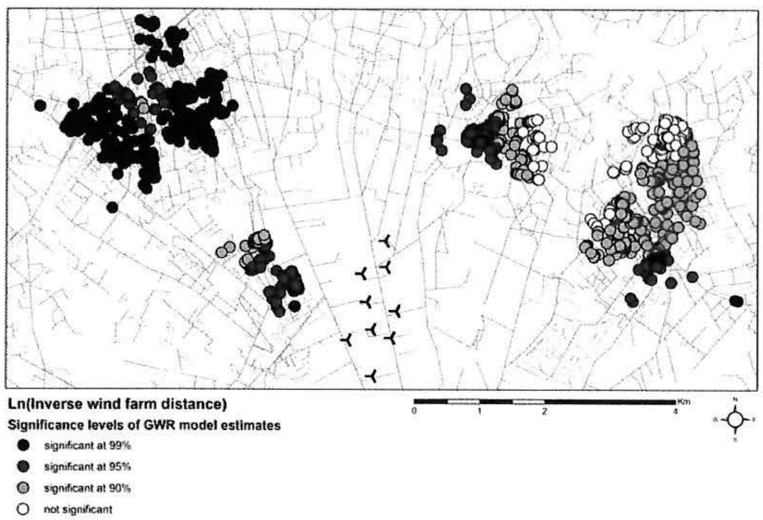


FIGURE 5
GWR model coefficients (a) and significance levels (b) for Ln (*Inverse wind farm distance*)

Figure 6(a) maps the GWR model coefficients for the variable *Visibility (No. of visible turbines)*. Thus, negative coefficients are solely located in the immediate vicinity of the wind farms site. As the properties in the close neighborhood to the site likely have an unimpaired view on several turbines, these findings seem reasonable. But considering the local distribution of the significance levels of the visibility variable (Figure 6(b)), no statistical significance of a visibility impact can be detected for the entire study area. Only in the immediate vicinity of the site significance levels strengthen, but still remain insignificant with p-values between 0.1 and 0.25. Overall, no statistical evidence was found for the particular consideration of wind farm visibility.

(a)

(b)

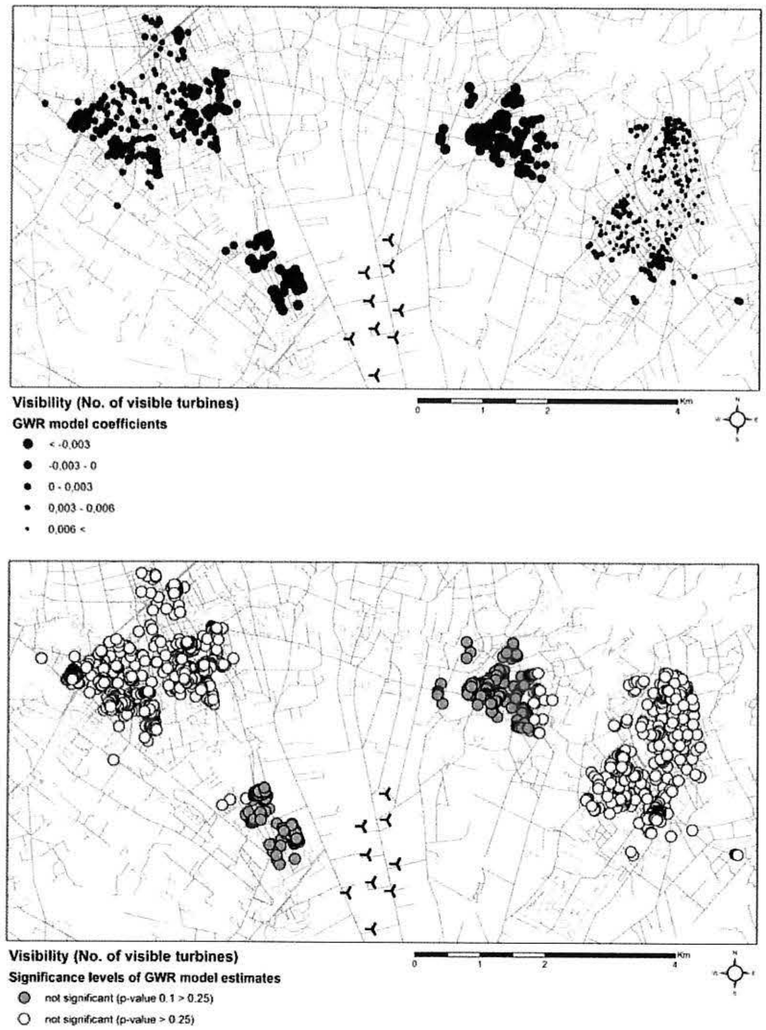


FIGURE 6
GWR model coefficients (a) and significance levels (b) for *Visibility (No. of visible turbines)*

In summary, the negative impact of wind farm proximity (measured by the inverse distance to the nearest turbine) that was found in the spatial fixed effects models could be confirmed, investigating the variable using the GWR method. Additionally, we found that proximity effects vary substantially across and within the cities. The investigation of the local coefficients of the visibility variable revealed that visibility has no significant impact on property values. Therefore, the results obtained in this case could not provide any validation for the relevance of applying a fixed viewshed effects model specification.

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. We investigated wind farm proximity by means of different spatial fixed effects model specifications, addressing spatial autocorrelation through spatially clustered omitted variables and spatial heterogeneity, and a local GWR model in order to further account for spatial heterogeneity caused by spatially varying relationships in the underlying data. As many hedonic pricing analyses investigating wind farm impacts focus on distance measures as a proxy for wind farm proximity, we also included variables capturing potential shadowing and visibility effects. We applied GIS techniques on the basis of high resolution geodata for the implementation of these variables.

We used four different spatial fixed effects models accounting for the underlying administrational and spatial structure of the study area, with a particular focus on a fixed viewshed effect specification. Comparing the models, the specification with the tightest controls for spatially clustered omitted variables performed best.

According to the estimation results provided by the spatial fixed effects regressions, there is statistical evidence for a negative impact of wind farm proximity measured by the inverse distance to the nearest turbine. Various distance dummies also indicated that negative impacts are mainly limited to properties in the immediate vicinity within 1.5 km. Due to lower significance levels of the distance dummy variables, local variations of coefficients and significance levels needed further consideration. Properties that were sold after the construction of the wind farm showed lower values compared to those which were sold before, indicating a negative post-construction effect. Alternatively, the announcement of the wind farm project had no measurable influence on property prices. The results obtained for the shadowing variables did not allow for a clear interpretation.

The fixed viewshed effects model provided the lowest values regarding the overall model performance, although the results were largely consistent with the other models. The major insight is that absorbing potential effects of visibility, the inverse distance to the nearest turbine still remains negatively significant.

The application of the GWR revealed a more complex picture of proximity effects through the weighting of spatial relationships and local variations in the data. The negative impact of wind farm proximity that was found using spatial fixed effects could be confirmed, applying the GWR method. Based on local GWR estimates, the negative effects are attributable to strong local influences of the wind farm site. Therefore, the local significance levels of wind farm distance provide evidence for a stronger negative impact on the city of Neuenkirchen than on the city of Rheine. Local coefficients and significance levels of the visibility variable revealed that visibility has no significant impact on property values. Therefore, the investigation of visibility by means of a GWR could not provide any validation for the relevance of applying a fixed viewshed effects model specification. Against this background, the results obtained by the fixed viewshed effects model remain ambiguous.

Nonetheless, further investigation of wind farm proximity and specifically visibility, also combining global and local spatial regression techniques, 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.

Future research on the impacts of wind farm proximity should essentially include a further investigation of spatial autocorrelation and spatial heterogeneity, also comparing and exploring the performance of different spatial models, such as spatial error and lag models vs. spatial fixed effects, and spatial weighting approaches. Further research incorporating local statistics, such as the GWR, along with established spatial model is needed, in order to underline the relevance of geographical techniques in economics.

As local authorities are increasingly aware of social acceptance problems in Germany, projects that involve civic participation in the planning process become increasingly important in order mitigate public protests. Therefore, it might be interesting to comparatively investigate wind farms projects that were planned with and without civic participation by means of the hedonic pricing approach.

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APPENDIX

TABLE A1

Statistics of the GWR model coefficients - Ln(*Inverse wind farm distance*)

	Minimum	25% Quartile	Median	75% Quartile	Maximum
Intercept	2.771	2.881	4.719	5.119	6.009
ln (Inverse *Wind farm distance)*	-.111	-.094	-.070	-.055	-.047
ln *Lot size*	.919	.948	1.056	1.080	1.087
Waterfront	-.061	.011	.037	.113	.147
Type single-family house	.115	.145	.164	.170	.184
Type duplex house	.200	.231	.260	.271	.282
Type row house	.159	.188	.194	.199	.216
Type multi-family house	.170	.235	.341	.359	.428
ln *CBD*	.001	.006	.032	.065	.082
ln *Supermarket*	-.001	.012	.074	.089	.110
ln *Commercial area*	-.066	-.041	.006	.023	.036
ln *School*	-.013	-.006	-.008	.061	.117
ln *Forestland*	-.069	-.052	-.037	-.006	.012
ln *Major road*	-.040	-.024	-.006	.005	.012
ln *Road*	.031	.042	.076	.088	.103
Street noise	-.139	-.077	-.052	-.042	-.019
ln *Railroads*	-.185	-.055	-.036	.020	.044
ln *Transmission line*	-.050	-.028	.018	.071	.189
ln *Lake*	-.045	-.039	-.012	.004	.022

TABLE A2

Statistics of the GWR model coefficients - *Visibility (No. of visible turbines)*

	Minimum	25% Quartile	Median	75% Quartile	Maximum
Intercept	3.412	3.505	5.335	5.690	6.733
Visibility (No. of visible turbines)	-.005	-.002	.003	.006	.011
ln *Lot size*	.921	.950	1.056	1.080	1.087
Waterfront	-.039	.046	.073	.142	.175
Type single-family house	.118	.150	.161	.168	.181
Type duplex house	.207	.241	.261	.271	.287
Type row house	.157	.185	.190	.196	.213
Type multi-family house	.182	.245	.342	.358	.426
ln *CBD*	.003	.007	.037	.072	.093
ln *Supermarket*	.000	.016	.082	.095	.144
ln *Commercial area*	-.068	-.053	.009	.028	.043
ln *School*	-.015	-.005	-.010	.050	.118
ln *Forestland*	-.066	-.051	-.036	-.006	.014
ln *Major road*	-.042	-.025	-.006	.005	.012
ln *Road*	.031	.042	.071	.084	.100
Street noise	-.125	-.068	-.053	-.042	-.016
ln *Railroads*	-.222	-.059	-.042	.021	.041
ln *Transmission line*	-.039	-.019	.024	.084	.214
ln *Lake*	-.045	-.037	-.007	.001	.019