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Optimal siting of onshore wind turbines: Local disamenities matter

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Abstract:

The deployment of onshore wind power is an important means to mitigate climate change. However, wind turbines also produce local disamenities to residents living next to them, mainly due to noise emissions and visual effects. Our paper analyzes how the presence of local disamenities affects the socially optimal siting of onshore wind power. The analysis builds on a spatial optimization model using geographical information system (GIS) data for Germany. Our results indicate a major spatial trade-off between the goals of minimizing electricity generation and disamenity costs. Considering disamenity costs substantially alters – and in fact dominates – the socially optimal spatial allocation of wind power deployment. This is because in Germany a) the spatial correlation between generation costs and disamenity costs is only moderately positive, and b) disamenity costs exhibit a larger spatial heterogeneity than the generation costs. These results are robust to variations in the level and slope of the disamenity cost function that we assume for the modeling. Our findings emphasize the importance of supplementing support schemes for wind power deployment with approaches that address local disamenties, e.g., compensation payments to local residents or minimum settlement distances.

Keywords: Externality; Germany; renewable energy, spatial optimization, wind power.

JEL codes: D62, Q42, Q51, Q53, R14

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1. Introduction

Onshore wind power is one of the key renewable energy sources that need to be developed at large scale to decarbonize the energy sector (Rogelj et al., 2018). An important question that arises in this context is how to site wind power generation capacity in order to attain deployment targets cost-effectively. This question has been discussed extensively for energy system costs. In this respect, siting decisions typically involve trade-offs between minimizing the levelized costs of electricity generation and other energy system costs (e.g., related to the extension of networks and storage). Such trade-offs have been studied for the European electricity system (Eriksen et al., 2017; Fürsch et al., 2013; Hagspiel et al., 2014; Schaber et al., 2012a; Schaber et al., 2012b; Schlachtberger et al., 2017; Schmid and Knopf, 2015) as well as for single countries like Germany (Agora Energiewende, 2013; Bucksteeg, 2019; Drechsler et al., 2017).

However, these studies largely ignore the fact that the deployment of onshore wind power also causes external environmental costs. These costs may be spatially heterogeneous, and may thus affect the optimal siting of wind power generation capacity. One important category of external environmental costs is related to local disamenities for residents living in the vicinity of wind turbines (for overviews, see Mattmann et al., 2016; Tabassum-Abbasi et al., 2014; Zerrahn, 2017). Local disamenities of onshore wind power include noise emissions, flicker effects, light reflections as well as changes to landscape aesthetics. There is a growing strand of empirical studies analyzing costs associated with local disamenities of onshore wind power. Studies rely on hedonic pricing models analyzing impacts on property values (e.g., Dröes and Koster, 2016; Dröes and Koster, 2021; Frondel et al., 2019; Gibbons, 2015; Heintzelmann and Tuttle, 2012; Jensen et al., 2014; Lang et al., 2014; Sunak and Madlener, 2016), life satisfaction approaches (Krekel and Zerrahn, 2017; von Moellendorff and Welsch, 2017), as well as willingness-to-pay analyses (e.g., Betakova et al., 2015; Brennan and van Rensburg, 2016; Drechsler et al., 2011; Guo et al., 2015; Jones and Eiser, 2010; Ladenburg and Dubgaard, 2007; Meyerhoff et al., 2010; Wen et al., 2018). There are two overarching insights from this literature. First, most studies find that the costs of local disamenities may be substantial. Second, local disamenities are often found to decline with increasing distances to wind turbines. Both insights point to costs of local disamenities being spatially heterogenous, depending on the distance to and the size of the affected population at a specific site. This suggests that costs of local disamenities should be included in spatial optimizations that aim to minimize the social costs of wind power deployment.

Against this background, our paper analyzes how the presence of local disamenities affects the optimal siting of onshore wind power. We particularly investigate the trade-off between minimizing local disamenities and electricity generation costs. We also aim to derive a spatial allocation that minimizes social costs, which we consider as the aggregate of both costs.

We apply our analysis to the case of Germany. Germany has experienced a vast growth of onshore wind power deployment in the past (Lauf et al., 2020). Onshore wind power is also considered as one of the key technologies for Germany's ongoing transition towards carbon neutrality (Agora Energiewende, 2020). Several studies using different empirical strategies provide evidence that wind power deployment produces significant disamenities in Germany (Drechsler et al., 2011; Frondel et al., 2019; Krekel and Zerrahn, 2017; Meyerhoff et al., 2010; Sunak and Madlener, 2016; von Moellendorff and Welsch, 2017). Based on this insight, we investigate how the consideration of local disamenties affects the socially optimal spatial allocation of wind power generation capacity in Germany.

Our analysis builds on a spatial optimization model using geographical information system (GIS) data. Using this model, we evaluate more than 100,000 potential sites, which are available for installing wind turbines in Germany if geographical and legal land-use constraints are considered. Each site is evaluated with respect to its potential electricity generation costs and local disamenities. Subsequently, we derive wind turbine allocations that are minimize electricity generation cost and local disamenities individually as well as the aggregate of both costs. We carry out this optimization for different deployment targets. Our results indicate that the consideration of local disamenities may significantly alter the socially optimal spatial allocation of onshore wind power. In fact, the socially optimal spatial allocation is close to the one that minimizes local disamenities. This is due to two reasons. First, the spatial correlation between generation and disamenity costs is only moderately positive in Germany. Second, disamenity costs exhibit a larger spatial heterogeneity in Germany than generation costs. Sensitivity analyses show that this result is fairly robust to variations in the calibration of the assumed cost function for local disamenities.

Our paper adds to a limited literature incorporating local disamenities into the spatial optimization of renewable energy deployment. The majority of existing assessments has been carried out using multi-criteria decision analyses. These assessments abstain from monetizing local disamenities. Instead, they solve the optimization problem by making rigid assumptions regarding the weights of different criteria. Some studies attach the same weights to all criteria (Baban and Parry, 2001; Eichhorn et al., 2019; Eichhorn et al., 2017). If differentiated weights are used, these are often chosen explicitly or implicitly by the authors themselves (Baban and Parry, 2001; Hanssen et al., 2018; Janke, 2010; Rodman and Meentemeyer, 2006; Tegou et al., 2010), or by a small group of experts (Ecer, 2021; Gigović et al., 2017; Höfer et al., 2017; Sánchez-Lozano et al., 2016; Watson and Hudson, 2015). Consequently, these studies do not allow for deriving spatial allocations that explicitly minimize social costs.

Only few studies incorporate external costs of local disamenities into a truly economic assessment of wind power deployment. Hevia-Koch and Jacobsen (2019) analyze how the levelized costs of electricity change for onshore wind power if local disamenity costs are considered next to generation costs. However, they do not carry out a spatial optimization, and are silent about spatial trade-offs. Several studies consider disamenity costs to determine socially optimal uniform minimum distances between wind turbines and human settlements in Germany. Drechsler et al. (2017) find that minimum distances should be as small as legally possible (800 m in their case). This result might suggest that local disamenities are not particularly important for the socially optimal siting of wind turbines. In contrast, Drechsler et al. (2011) and Salomon et al. (2020) find moderate minimum settlement distances (between 1,000 and 1,200 m) to be socially optimal. These outcomes indicate that local disamenities can matter for the socially optimal allocation of wind turbines to some extent. Yet, all three studies do not allow for a comprehensive understanding of spatial trade-offs and optimal spatial allocations because they do not carry out unconstrained optimizations. Looking only at different options for uniform minimum distances significantly reduces the solution space. This is a particular problem because uniform minimum distances are a fairly inefficient instrument to address local disamenities. They do not allow accounting for differences in the number of residents affected at a specific site. Moreover, they treat residents living within (outside) the minimum distance equally, irrespectively of how far away from a wind turbine they actually live. Implicitly, these studies thus attach a relatively high shadow price to internalizing local disamenities. As a consequence, they may underestimate the importance of local disamenities for an optimal spatial allocation of wind turbines. Their contribution to assessing spatial trade-offs and optimal spatial allocations of wind power deployment is thus limited.

Grimsrud et al. (2021) integrate local disamenity costs into a spatially explicit, unconstrained optimization of wind power deployment in Norway. They find that the integration of local disamenity costs substantially alters the socially optimal allocation of wind power deployment. They explain that this result is primarily due to the local disamenities produced by the grid extensions necessary to accommodate wind power deployment. Grimsrud et al. (2021) use a simplified disamenity cost function. This function differs between sites depending on the population of the municipality in which the wind turbine is located. However, they ignore the actual distance between a wind turbine site and a household.

We go beyond the study by Grimsrud et al. (2021) by determining a local disamenity cost function which is specific for each of the more than 100,000 potential sites in Germany, depending on the exact size of and distance to the affected population nearby. Our approach thus allows for a much more precise spatial assessment of optimal wind power deployment and related trade-offs. Our results for Germany are in line with the basic finding of Grimsrud et al. (2021) for Norway that the consideration of local disamenity costs substantially affects the optimal spatial allocation of wind turbines. This is despite the fact that we, in contrast to their study, ignore local disamenities produced by grid extensions necessary for wind power deployment. In our study, local disamenties dominate the optimal spatial allocation because heterogeneity of local disamenities across individual sites is much more pronounced than for generation costs. Our analysis also adds to the existing studies because we do not only look at a specific deployment target which is to be attained at least cost. Instead, we also investigate how spatial trade-offs and the optimal spatial allocation develop with increasing deployment levels.

The remainder of the paper is organized as follows: Section 2 introduces our methodological approach and data in more detail. Section 3 presents the quantitative results of our spatial optimization. Section 4 discusses the results critically. Section 5 concludes.

2. Model

2.1 Optimization approach

The analysis is conducted with the General Algebraic Modeling System (GAMS) to solve three different kinds of optimization problems: Spatial allocations of wind turbines are determined which minimize total 1) local disamenity costs, 2) generation costs, and 3) social costs, defined as the sum of disamenity and generation costs, across all wind turbines that need to be deployed for attaining an exogenously set generation target. The corresponding objective functions for the three optimizations are:

$$\min_{WT_{i=1},\dots,WT_{i=n}} \sum_{i=1}^{n} C_i^{\mathrm{dis}} * WT_i \tag{1}$$

$$\min_{WT_{i=1},\dots,WT_{i=n}} \sum_{i=1}^{n} C_i^{\mathrm{gen}} * WT_i \tag{2}$$

$$\min_{WT_{i=1},\dots,WT_{i=n}} \sum_{i=1}^{n} (C_i^{\mathrm{dis}} + C_i^{\mathrm{gen}}) * WT_i \tag{3}$$

each subject to

$$GT \leq \sum_{i=1}^{n} \mathrm{AEP}_{i} * \mathrm{WT}_{i} \tag{4}$$

C_i^{dis} are the local disamenity costs arising if a turbine is installed at site i. C_i^{gen} are the respective generation costs. WT_i is a binary selection variable for installing a wind turbine at site i: It is unity ($WT_i = 1$) if a site is selected for installing a wind turbine to solve the optimization problem, and zero ($WT_i = 0$) otherwise. GT is the exogenously set generation target. The sum of the annual energy production AEP_i of the wind turbines installed at all sites selected under the respective optimization problem must be equal to (or larger than) this generation target. Thus, the generation target GT defines the level of total electricity generation and thereby allows for a comparison of the results for the different objective functions that are subject to the same generation target. We increase GT stepwise for consecutive model runs, ranging from zero (meaning that no site needs to be selected for installing a wind turbine) up to the maximum level of electricity generation (meaning that wind turbines are installed at all potential sites).

In addition, we calculate 'isoquants' for each generation target. An isoquant for a given generation target represents optimal multi-criteria solutions that are associated with objective functions which lie between the mono-criterial optimizations calculated with equations (1) and (2). For this, an additional weighting factor β with $\beta \in (0; 0.1; \ldots; 1)$ is introduced to the objective function shown in eq. (3) so that a stepwise shifting in the weight from one cost criterion to the other is set up:

$$\min_{WT_{i=1},\ldots,WT_{i=n}} \sum_{i=1}^{n} [\, \beta * C_i^{\mathrm{dis}} + (1 - \beta) * C_i^{\mathrm{gen}} \,] * WT_{\mathrm{i}} \tag{5}$$

Equation (5) is also solved subject to the constraint (4).

2.2 Data and calibration

2.2.1 Potential sites for onshore wind energy

For the identification of the potential sites for wind turbines across Germany, we utilize the results of a green field allocation performed and published by Masurowski (2016). He first of all identified potential areas suitable for the installation of wind turbines. For this purpose, he considered GIS data for a comprehensive set of land-use constraints. He included techno-physical constraints (e.g., areas occupied by settlements, roads and other infrastructure, and areas with excessive slopes), as well as legal constraints (e.g., nature reserves and safety distances to airports). Subsequently, a GIS-based application called “MaxPlace” distributed potential wind turbines to specific sites within the identified potential areas so that a maximum number of wind turbines could be allocated (Masurowski, 2016). A single site is thus eligible for installing one wind turbine. This data set has been used by a range of other studies published in recent years (Drechsler et al., 2017; Eichhorn et al., 2017; Masurowski et al., 2016).

Potential areas and sites also depend on the turbine specifications, namely the noise emissions of the turbine type and the total height of the turbine. Both characteristics determine minimum distances to settlement areas in Germany to comply with legal requirements for the protection of residents. For our analysis, we use the turbine type E101 manufactured by Enercon, which is a widely used wind turbine in the 3 MW class with a hub height of 135 m and a rotor diameter of 101 m (Enercon, 2015). This turbine is certified for operation under all wind conditions in Germany. It may be noted that in practice the selection of turbine types commonly depends on the wind conditions onsite as wind turbines have been especially developed for low and high wind speeds (Hirth and Müller, 2016; Johansson et al., 2017). Yet, in order to enable our modeling, we simplify by assuming only one wind turbine type. To comply with standards for the protection of residents from noise emissions, we exclude all sites from our analysis that are placed within a distance of 800 m to a settlement structure. This value is also assumed by Drechsler et al. (2017) as minimum settlement distance in Germany for the reference turbine (E101) that we consider.

Eventually, this procedure yields 106,497 potential sites for wind turbines in Germany (see Figure 1). Throughout our analysis, we will primarily look at trade-offs and optimal allocations for Germany as a whole. In the sensitivity analyses, we will also investigate how trade-offs and optimal allocations vary if only individual German states are considered. Table 1 illustrates how potential sites are spread across Germany’s states. For each site, annual energy production AEP_i, generation costs C_i^{gen}, and local disamenity costs C_i^{dis} are calculated as described in the following.

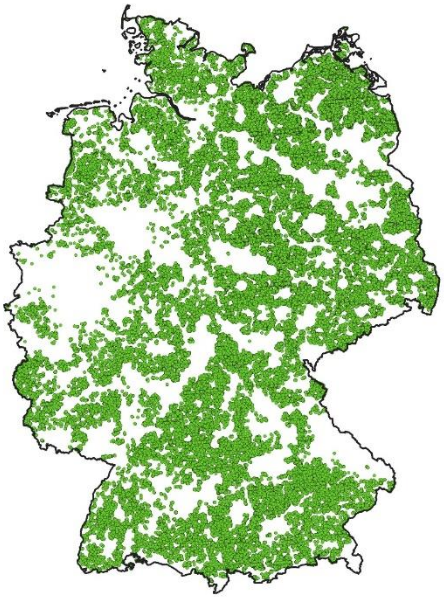


Figure 1: Potential sites for wind turbines in Germany

State	**No. of potential sites**	**Potential annual energy production (in TWh)**
Baden Württemberg	7,711	36.74
Bavaria	13,928	65.66
Berlin	4	0.03
Brandenburg	16,973	126.74
Bremen	6	0.06
Hamburg	3	0.03
Hesse	6,465	44.21
Lower Saxony	11,912	107.87
Mecklenburg Western Pomerania	13,104	119.05
Northrhine Westfalia	1,479	11.67
Rhineland Palatinate	3,905	23.25
Saarland	121	0.67
Saxony	4,637	36.50
Saxony Anhalt	17,433	136.05
Schleswig Holstein	2,503	23.91
Thuringia	6,313	45.55
Total	**106,497**	**777.72**

Table 1: Potential sites for wind turbines and resulting potential annual energy production by German states

2.2.2 Annual energy production

Based on the power curve of the Enercon E101 3.0 MW wind turbine (Enercon, 2015) and high resolution wind climate data provided by DWD (2014), we calculate the theoretical annual energy production AEP_i for each potential site (Eichhorn et al., 2017). The actual AEP_i under realistic operation conditions is likely below this the theoretical level. Inter alia, this may be due to generation losses at specific sites resulting from wake turbulences induced by the operation of other wind turbines in close proximity, as well as downtimes for maintenance and repairs. In our analysis, we account for these factors by reducing the AEP_i uniformly by 15% for every potential site and turbine (a similar approach is used, e.g., by McKenna et al., 2014; Sliz-Szkliniarz et al., 2019).

The total annual energy production when wind turbines are installed at all potential 106,497 sites across Germany amounts to 778 TWh. This is more than seven times the production provided by onshore wind power in Germany in 2020 (Fraunhofer ISE, 2021). Table 1 also differentiates the possible total annual energy production between Germany's states. The AEP_i is not only relevant for the subsequent assessment of specific generation costs and local disamenity costs. It is also required to carry out the different optimizations subject to specific generation targets GT.

2.2.3 Generation costs

Following the approach of Kost et al. (2018), generation costs C_i^{gen} for a wind turbine at site i are computed as the present value of investment costs and operation and maintenance costs over the typical economic lifetime of a wind turbine of 20 years:

$$C_i^{gen} = I_0 + \sum_{t=1}^{5} \frac{A_{1t}}{(1+r)^t} + \sum_{t=6}^{20} \frac{A_{2t}}{(1+r)^t} \tag{6}$$

I_0 is the investment costs in the first year of operation (assumed value: 1,567 EUR/kW). A_{1t} is the annual total operation and maintenance costs per year t for the first 5 years in operation (assumed value: 30 EUR/kW), A_{2t} the annual total operation and maintenance costs per year t for the remaining 15 years in operation (assumed value: 50 EUR/kW). The annual discount rate r is assumed to be 3%. The utilized parameter values are taken from Wallasch et al. (2015). The resulting present value of generation costs amounts to 7.1 million EUR per wind turbine. These generation costs are assumed to be the same for all sites. Dividing C_i^{gen} by $\sum_{t=1}^{20} \frac{AEP_i}{(1+r)^t}$ yields the site-dependent specifc generation costs per unit of generation (i.e., the levelized cost of electricity).

2.2.4 Disamenity costs

To determine the local disamenity costs C_i^{dis} of installing a wind turbine at a site i, we first assess a disamenity cost function c_h^{dis} for an individual household h as a function of the distance of the household to the wind turbine site. This function is assumed to be identical for all sites under consideration and reflects increasing marginal disamenity costs with decreasing resident-turbine-distances as they are typically observed in willingness-to-pay analyses (see the review by Wen et al., 2018). The chosen functional form for c_h^{dis} is a hyperbola, as, e.g., in Drechsler et al. (2011). The shape of the used hyperbolic cost function is determined drawing on different values found in the literature for Germany.

First, the findings of a life-satisfaction study by Krekel and Zerrahn (2017) suggest that a wind turbine does not cause local disamenities for households if the distance between the turbine and the household is larger than about 4,000 m. Using a hedonic pricing approach, Gibbons (2015) finds a similar value for England and Wales. Therefore, we assume that the hyperbolic cost function runs to zero at 4,000 m. Second, for determining the slope of c_h^{dis}, the hyperbolic function is fitted to the results of an economic valuation study carried out in Germany by Meyerhoff et al. (2010). They conducted choice experiments and derived monthly values for the willingness to pay (WTP) of people for different marginal changes of buffer distances (from 750 m to 1100 m, and from 750m to 1500m) between wind turbines and settlements. Third, we scale the hyperbolic cost function drawing on the more recent data by Krekel and Zerrahn (2017). They estimate for Germany that on average a household experiences disamenity costs of 258 Euro per year, or 21.50 Euro per month, if a wind turbine is located within a radius of 4,000 m to the household. Therefore, we scale the assumed hyperbolic function such that it has a value of 21.50 Euro at 2,500 m. The distance of 2,500 m is chosen here because it is the mean value of the 4,000 m cut-off and 1,000 m. The value of 1,000 m is considered here because at many places in Germany wind turbines are not sited closer to settlements than 1,000 m due to regional minimum distance requirements (FA Wind, 2020).

Altogether, the aforementioned study values are cast into the following hyperbolic function:

$$c_h^{dis}(d_h) = 90\ \mathrm{Euro}\left(\frac{1054\ \mathrm{m}}{d_h - 543\ \mathrm{m}} - 0.3\right) \tag{7}$$

for the monthly disamenity costs c_h^{dis} (measured in Euro) accruing to household h due to a wind turbine installed in distance d (measured in m). The function is shown in Figure 2 (bold solid line A).

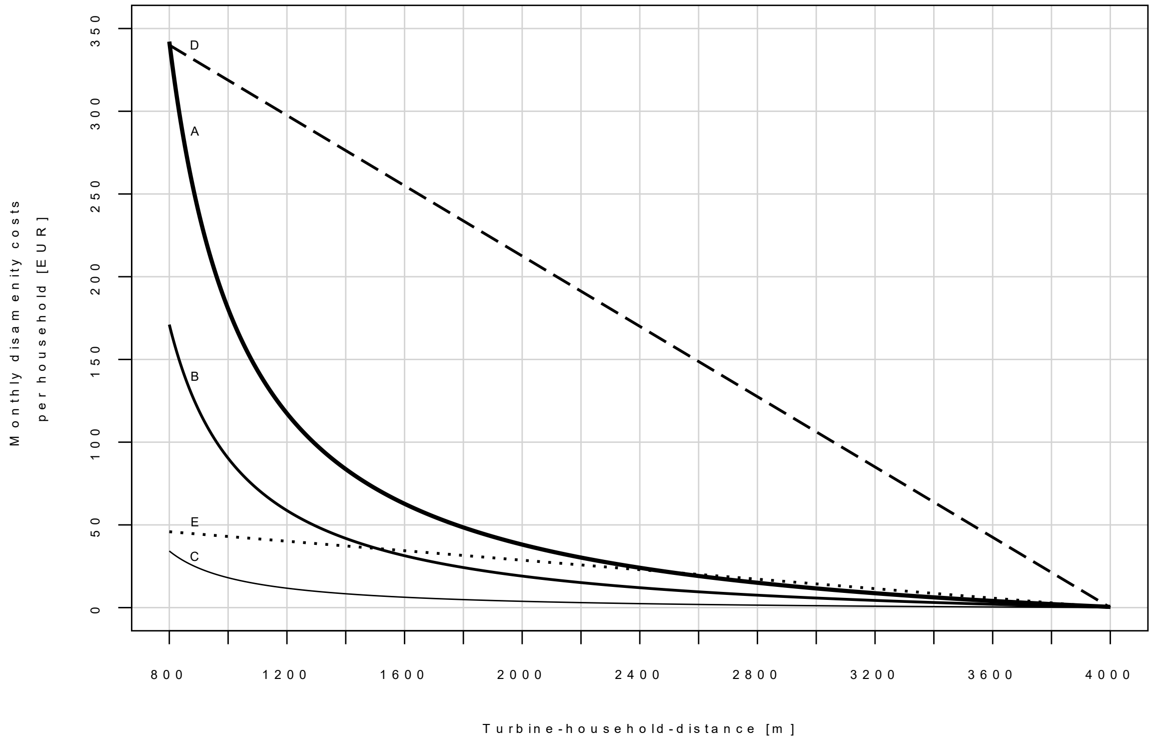


Figure 2: Assumed monthly disamenity costs $C_h^{\mathbf{dis}}$ (in Euro) accruing to a household h from a wind turbine depending on the turbine-household-distance d (in m) as assumed for the base case (bold solid line) and the sensitivity analyses (dashed, dotted, and thinner solid lines)

The present value of the total local disamenity costs imposed on an individual household by an individual wind turbine over its economic lifetime of 20 years, c_{h20}^{dis}, can be computed by aggregating and discounting the monthly disamenity costs $c_h^{dis}(d_h)$ for a time period of 20 years:

$$c_{h20}^{dis} = \sum_{t=1}^{20} \frac{12 * c_h^{dis}(d_h)}{(1{,}03)^t} \tag{8}$$

As before, we assume a discount rate of $r = 0.03$ (see, e.g., Drechsler et al., 2011).

Finally, the local disamenity costs over 20 years of installing a wind turbine at site i, C_i^{dis}, is determined by aggregating the distance-dependent disamenity costs for 20 years c_{h20}^{dis} of each household located in the 4,000 m-radius around this site. The resulting local disamenity cost estimate is site-specific as it depends on the amount of and distance to households living in the vicinity of the wind turbine site. The estimate can be transferred into a specific disamenity cost per unit of electricity generated at site i by dividing C_i^{dis} by $\sum_{t=1}^{20} \frac{AEP_i}{(1+r)^t}$ (as for specific generation costs above).

Apart from the described hyperbolic cost function, we also consider further disamenity cost functions in sensitivity analyses to account for uncertainties in monetizing local disamenity costs. We are aware that our calibration may overestimate local disamenity costs for various reasons. First, this may be due to the fact that we scale the household disamenity cost function c_h^{dis} based on life-satisfaction data. As Krekel and Zerrahn (2017) point out, this approach tends to deliver higher monetary estimates of external costs than, for example, hedonic pricing approaches. Moreover, we assume annual local disamenity costs to remain constant over the lifetime of a wind turbine. However, there is some evidence of habituation effects: Over time, people may feel less disturbed by existing wind turbines. For example, Krekel and Zerrahn (2017) find that local disamenities may decay five years after the installation of a wind turbine. Overall, empirical evidence on habitation effects is inconclusive, though (see the review by Zerrahn, 2017). Similarly, local disamenities arising over the lifetime of a wind turbine may be less important if a higher discount rate is assumed. More generally, the results of monetary estimations of disamenity costs tend to vary a lot across studies (see the reviews by Mattmann et al., 2016; Wen et al., 2018; Zerrahn, 2017). To account for these uncertainties, we reduce all values of the disamenity cost function c_h^{dis} as provided in eq. (7) evenly by 50% and 90%, respectively (see the thinner solid lines B and C in Figure 2). The effects of theses variations for the hyperbolic cost function are twofold: first, both variations generally lead to lower cost levels. Second, they also result in less bended curves, reflecting lower increases in marginal costs with decreasing distances than in the base case of eq. (7). Thus, spatial heterogeneity of local disamenity costs is also reduced.

In order to further control for the spatial heterogeneity constructed by the assumed hyperbolic function form, we also assume two linear household-specific disamenity cost functions. The first linear variation assumes that the disamenity costs have rather a high level. It has the same value as the hyperbolic cost function of eq. (7) at 800 m and a value of zero at 4,000 m (see dashed line D in Figure 2):

$$c_h^{\mathrm{dis}}(d_h) = \frac{17}{160}\,\mathrm{Euro/m}\;(4000\ \mathrm{m} - d_h) \tag{9}$$

The second linear variation assumes a much lower cost level than in the linear function of eq. (9). For this, we assume a linear function which has the same value as the hyperbolic cost function of eq. (7) at 2,500 m (21.50 Euro) and a value of zero at 4,000 m (see dotted line E in Figure 2):

$$c_h^{\mathrm{dis}}(d_h) = \frac{43}{3000}\,\mathrm{Euro/m}\;(4000\ \mathrm{m} - d_h) \tag{10}$$

3. Results

3.1 Results with basic assumptions

3.1.1 Spatial trade-offs between minimizing total generation costs and total disamenity costs

We will first shed light on the trade-off between minimizing total generation costs and total disamenity costs for Germany under our basic assumptions. Figure 3 illustrates the results of our analysis for our basic assumptions. The dashed blue curve depicts how the present value of total generation costs (x-axis) and of total disamenity costs (y-axis) evolve with increasing levels of wind power deployment if the spatial allocation is chosen such that total *generation costs* are minimized. The dotted yellow curve depicts the same relationship if total *disamenity costs* are minimized for increasing generation targets. Both curves thus represent optimal deployment trajectories with respect to either cost criterion. By definition, the values of both curves coincide if no wind power is deployed (point of origin in Figure 3), or if wind turbines are installed at all potential sites (upper right point of the graph in Figure 3 with a generation of 778 TWh/a). There would be no spatial trade-off between minimizing total generation costs and total disamenity costs if the curves overlapped perfectly between both points. No matter which criterion was chosen for optimization, the same sites would then be selected for a given generation target. In turn, the larger the gap between both curves, the larger is the trade-off between minimizing either cost in absolute terms.

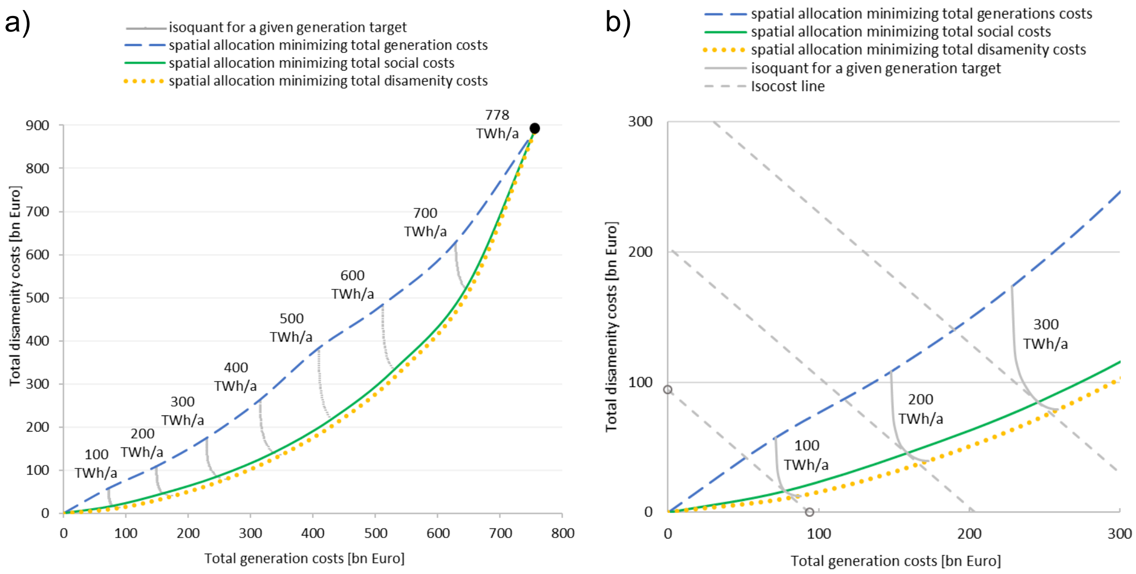


Figure 3: Total generation costs, total disamenity costs, and isoquants for different optimization criteria and generation targets: a) full range of possible generation targets, b) detail for rather low generation targets

Our model results depicted in Figure 3 therefore suggest a substantial trade-off between minimizing total generation and total disamenity costs for wind power deployment in Germany. Take, for instance, a generation target of 200 TWh/a. This is slightly below the generation from onshore wind power which is projected to be necessary in 2040 to achieve carbon neutrality in Germany by 2050 (Agora Energiewende et al., 2020). If total generation costs are minimized, this generation target involves total generation costs of 148 billion Euro and total disamenity costs of 108 billion Euro. Choosing a spatial allocation that attains the same generation target at minimum total disamenity costs, increases total generation costs to 173 billion Euro and reduces total disamenity costs to 39 billion Euro.

In absolute terms, the trade-off between minimizing total generation costs and minimizing total disamenity costs is small for low generation targets, i.e., near the point of origin of the graph in Figure 3. This is because for low generation targets, a comparatively high share of the sites chosen under both optimization criteria exhibit both low generation and low disamenity costs. Hence, the spatial allocations of wind turbines resulting from both optimizations largely overlap. This is illustrated in Figure 4 which depicts the spatial allocations minimizing either total generation costs or total disamenity costs for a generation target of 200 TWh/a. Both allocations are largely clustered in the North of Germany. Yet, minimizing total disamenity costs (Figure 4b) instead of total generation costs (Figure 4a) leads to a shift of wind turbines from the windier Northwest to the less densely populated Northeast of Germany. This observation notwithstanding, the trade-off may already be substantial in relative terms for the generation target of 200 TWh/a. In fact, switching from minimizing total generation costs to minimizing total disamenity costs increases total generation costs by 17% and more than halves total disamenity costs.

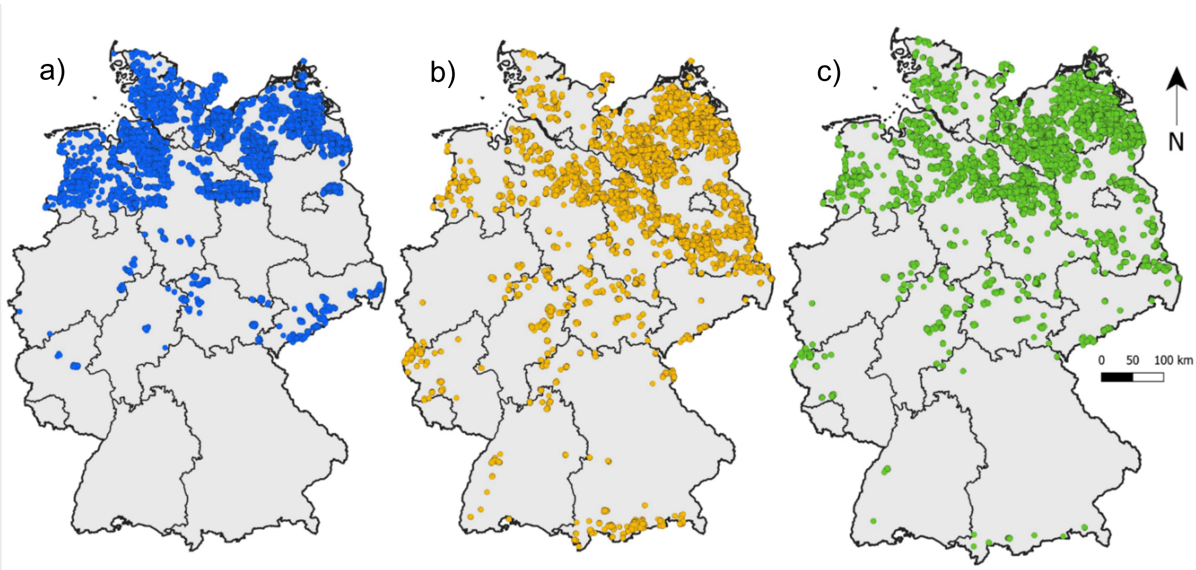


Figure 4: Spatial allocation of wind turbines for a deployment level of 200 TWh/a if total generation costs are minimized (map a), if total disamenity costs are minimized (map b), and if total social costs are minimized (map c).

The overlap between windy sites and sites with low disamenities at first declines with increasing generation targets. Therefore, the trade-off between both optimization criteria initially increases in absolute terms (illustrated by the increasing gap between the dashed blue and the dotted yellow curve in Figure 3). It peaks for a generation target of around 500 TWh/a. Beyond this peak, the trade-off decreases again in absolute terms with further increasing generation targets. This is due to that fact that the degrees of freedom for choosing sites vanish if very high generation targets need to be reached.

The trade-off between both cost criteria can also be illustrated by the 'isoquants' derived for specific generation targets (see the grey lines in Figure 3). An isoquant illustrates how a certain level of generation (the 'output') can be reached by different combinations of generation and disamenity costs (the 'inputs'). In other words, the isoquant's slope illustrates the marginal rate of substitution between total generation costs and total disamenity costs for a given generation target. The extreme points of the isoquant are located on the dashed blue curve (indicating globally minimal total generation costs for a given generation target) and on the dotted yellow curve (indicating globally minimal total disamenity costs for a given generation target).

3.1.2 Minimizing total social costs

We will now turn to analyzing the spatial allocation that minimizes total social costs, i.e., the sum of total generation and total disamenity costs. The solid green curve in Figure 3 indicates the expansion path for wind power deployment which minimizes total social costs. Technically, this expansion path corresponds to the tangent points between the isoquants and the isocost lines for different generation targets (see Figure 3b).

Notably, the socially optimal solutions (solid green curve) are relatively close to those that minimize total disamenity costs (dotted yellow curve). This indicates that disamenity costs dominate the socially optimal allocation of wind turbines. This is also visible from the 'isoquants' (grey curves) in Figure 3. For a large part, these are very steep. In these sections, disamenity costs can be reduced significantly at the expense of relatively modest increases in generation costs. In addition, comparing Figure 4b and 4c illustrates for the generation target of 200 TWh/a that sites chosen to minimize total disamenity costs are largely identical to those chosen if total social costs are minimized.

Figure 5 visualizes total social costs for the three optimization approaches as a function of the generation target. As can be seen, the allocations that minimize total social costs (solid green curve) and the allocations that minimize only total disamenity costs (dotted yellow curve) lead to very similar total social costs. Both approaches clearly outperform the approach that minimizes only total generation costs (dashed blue curve). For a generation target of 200 TWh/a, total social costs are 204 billion Euro if an allocation is chosen that minimizes total social costs, and 212 billion Euro if only total disamenity costs are minimized. These values compare to 257 billion Euro if only total generation costs are minimized. Thus, considering also local disamenities when choosing a spatial allocation for onshore wind power in Germany may help to substantially reduce total social costs of wind power deployment by as much as 26%, compared to an allocation decision only considering generation costs.

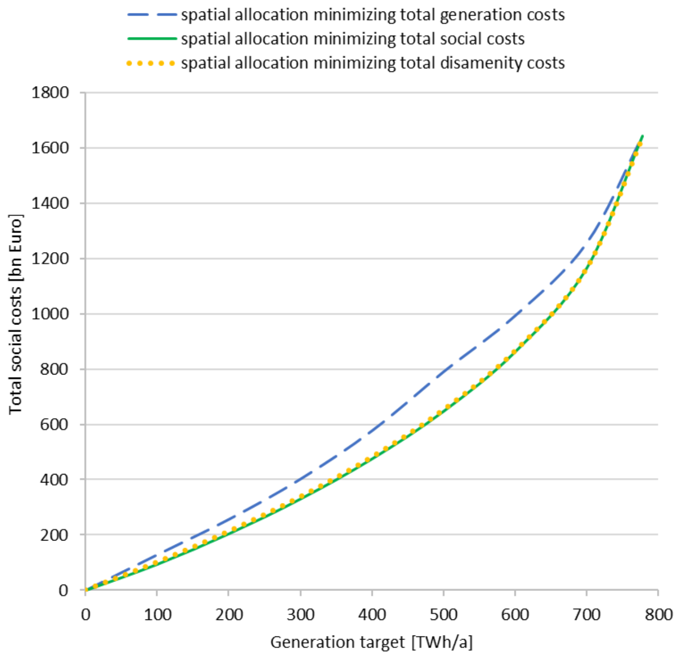


Figure 5: Total social costs of wind power deployment as a function of the generation target, for allocations minimizing either total generation costs, disamenity costs, or social costs

But why do disamenity costs dominate the socially optimal allocation of wind power deployment in Germany? The average specific generation and disamenity costs per kWh over all potential sites in Germany are quite similar (see the box plots in Figure 6). Therefore, differences in the average magnitude of both cost types cannot explain why the spatial allocation minimizing social costs is to a large extent dependent on a minimization of disamenity costs in Germany. What differs between both types of costs, however, is the spread of possible values across potential sites, i.e., their spatial heterogeneity. It is much higher for disamenity costs than for generation costs (see also the box plots in Figure 6). The disamenity costs are driven both by settlement structure and population density. The application of our basic hyperbolic disamenity cost function (curve A in Figure 2) leads to disamenity costs as low as zero at some sites in very sparsely populated areas, and quite high disamenity costs close to agglomerations where many households may be affected by a single wind turbine nearby. In contrast, the spread in generation costs is less pronounced, i.e., the degree of spatial heterogeneity in wind yield is relatively less distinct. The differences in spatial heterogeneity combine with the fact that there is a substantial spatial trade-off between minimizing generation costs and disamenity costs, as has been pointed out above (also illustrated by the Pearson correlation coefficient of 0.526 in Figure 6). When choosing socially optimal sites for wind power deployment, it is then more important to account for the (higher) spatial heterogeneity in disamenity costs than to account for the (lower) spatial heterogeneity of generation costs. This explains why the socially optimal spatial allocation of wind power deployment is similar to the one that minimizes total disamenity costs.

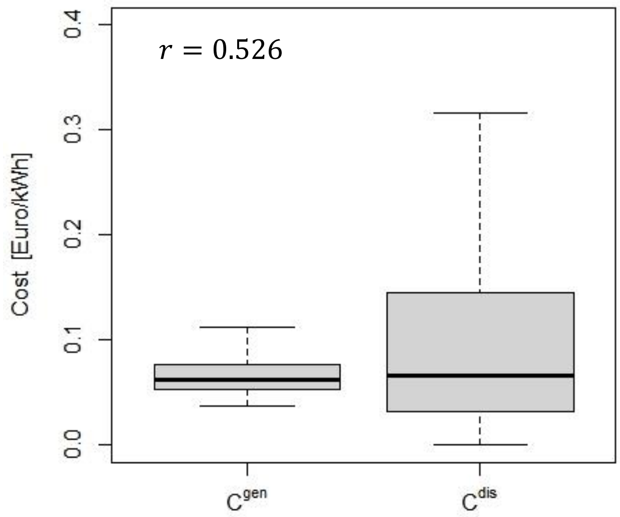


Figure 6: Box whisker plot with median and quartiles and Pearson correlation coefficient *r* of specific generation costs C^{gen} and disamenity costs C^{dis} (in Euro/kWh) across all potential sites

3.2 Sensitivity analyses

The results obtained so far may respond sensitively to the basic assumptions underlying our model. In the following, we will analyze how variations in the form of the disamenity cost function and in the geographic context affect our results.

3.2.1 Varying the form of the disamenity cost function

The observed dominant effect of disamenity costs on the socially optimal allocation may be due to the calibration of our disamenity cost function. First, when scaling the disamenity cost function for an individual household, c_h^{dis}, we may have overestimated the monetary value level of the disamenities. This may be due to methodological reasons, the ignorance of habituation effects, or a low discount rate (see Section 2.2.4). Scaling down the disamenity cost function may reduce the importance of the potential sites' proximities to households and the associated disamenity costs for the socially optimal allocation. Second, the large spatial heterogeneity observed for disamenity costs (see Figure 6) may at least partially be an artefact of assuming a hyperbolic function. This assumption increases the disamenity produced by a wind turbine more than proportionally with a decreasing distance to the household. Assuming a less bended function may reduce the spatial heterogeneity of the sites' disamenity costs. This may also lead to a weaker impact of the potential sites' proximities to households and the associated disamenity costs on the socially optimal allocation of wind power deployment.

We first scale down the disamenity cost function c_h^{dis} for an individual household by 50% and 90%, respectively (see the two thinner solid curves B and C in Figure 2). This approach reduces the level of disamenity costs, and also reduces spatial heterogeneity. The results of the spatial optimization using these functional forms are provided in Figure 7. Halving the level of disamenity costs for each potential wind turbine site hardly changes the picture, if compared to the results with the initially made cost level assumption (compare Figure 7a with Figure 3a). Although the level of total disamenity costs is clearly lower than in the base case (compare y-axes in Figure 7a and 3a), the socially optimal spatial allocation (solid green curve in Figure 7a) is still fairly close to the one that minimizes total disamenity costs (dotted yellow curve in Figure 7a). The reduction of the disamenity cost level by 90% compared to the original value leads to a noticeable shift of the socially optimal spatial allocation towards the one that minimizes generation costs (Figure 7b). Yet, the spatial allocation minimizing total social costs (solid green curve in Figure 7b) is still clearly different from the one that minimizes total generation costs (dashed blue curve in Figure 7b). So even in this case, disamenity costs are still highly relevant for choosing optimal sites for wind turbines if total social costs are to be minimized. Consequently, our results seem to be fairly robust to the variations in the scale of the household-specific local disamenity function c_h^{dis}, which reduce both the level and the spatial heterogeneity of disamenity costs.

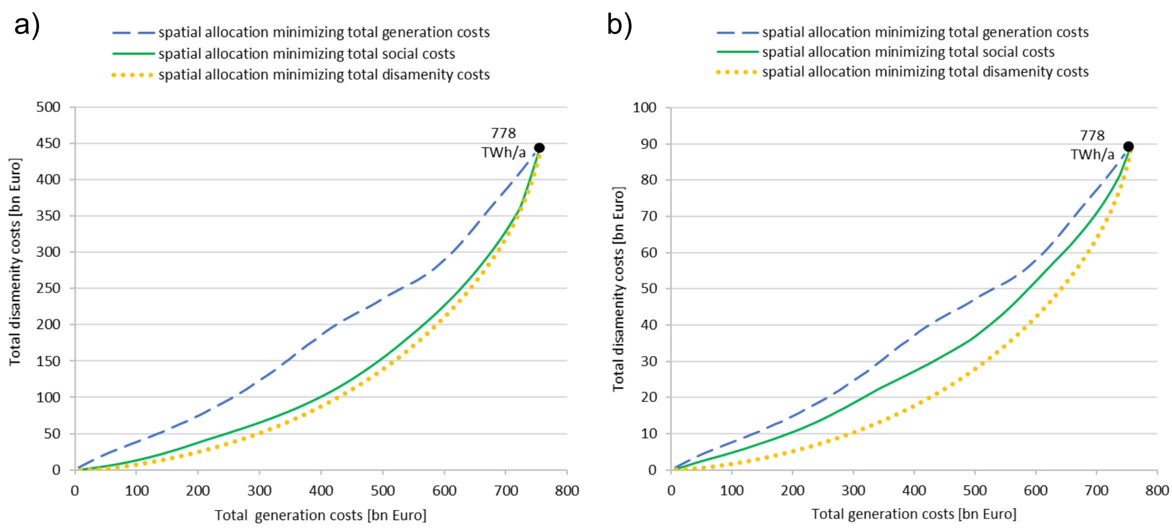


Figure 7: Optimization results for disamenity costs reduced by a) 50% and b) 90%

To further control for spatial heterogeneity induced by the choice of the functional form, we also optimize the spatial allocation of wind power deployment using a linear instead of a hyperbolic disamenity cost function for an individual household, c_h^{dis}. We consider a linear function with high disamenity costs (dashed line D in Figure 2) and one with low disamenity costs (dotted line E in Figure 2). Compared to the basic calibration of the disamenity cost function (solid line A in Figure 2), the high-linear cost function smoothes spatial heterogeneity of the potential sites' disamenity costs (possibly reducing the relevance of the potential sites' proximities to households and the associated disamenity costs for the social cost optimization). Yet, it also increases the total level of disamenity costs (possibly increasing the relevance of the potential sites' proximities to households and the associated disamenity costs for the social cost optimization). The low-linear cost function, in contrast, simultaneously decreases spatial heterogeneity and the total level of disamenity costs (both effects possibly reducing the relevance of the potential sites' proximities to households and the associated disamenity costs for the social cost optimization), compared to the basic functional form.

The optimization results for both linear functional forms are provided in Figure 8. If the high-linear disamenity cost function is assumed (Figure 8a), the socially optimal allocation (solid green curve) even more closely overlaps with the one that minimizes total disamenty costs (dotted yellow curve), compared to the results with our basic assumptions (Figure 3). That is, disamenity costs dominate the spatially optimal allocation even more. Hence, the effect of an overall higher level of disamenity costs more than offsets the lower spatial heterogeneity of disamenity costs assumed with this functional form. If the low-linear cost function is assumed, the importance of disamenity costs hardly changes (Figure 8b), compared to the outcomes with our basic assumption (Figure 3). The socially optimal allocation (solid green curve) remains close to the one minimizing total disamenity costs (dotted yellow curve).

Overall, these sensitivity analyses suggest that our results do not hinge strongly on whether the household disamenity cost function c_h^{dis} is hyperbolic or linear. This implies that the spatial heterogeneity of disamenity costs across potential sites primarily stems from spatial differences in the settlement structure and population density. It is primarily these geographic factors which drive the remarkable differences between sites regarding their local disamenity costs.

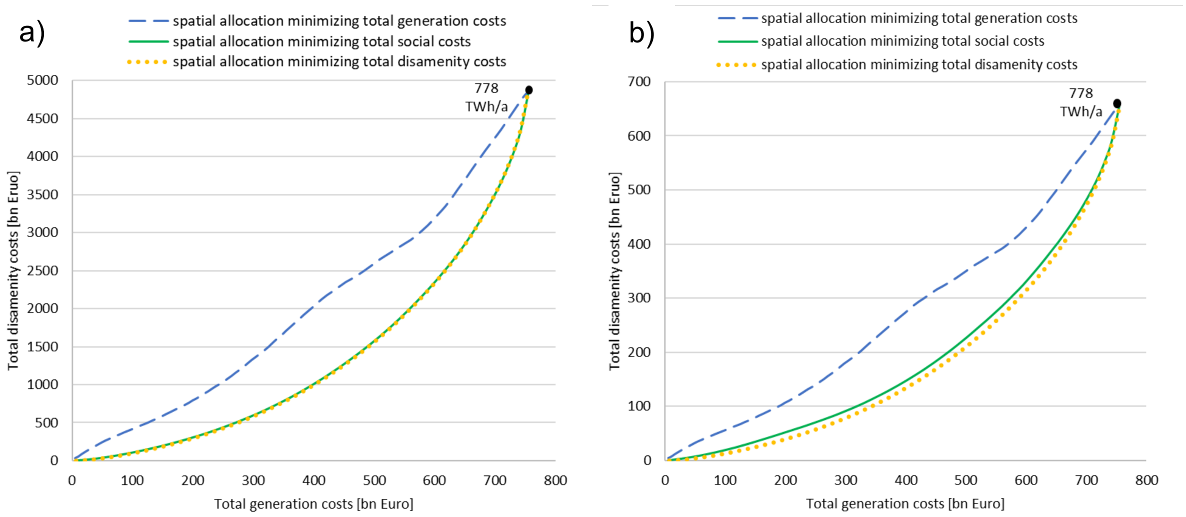
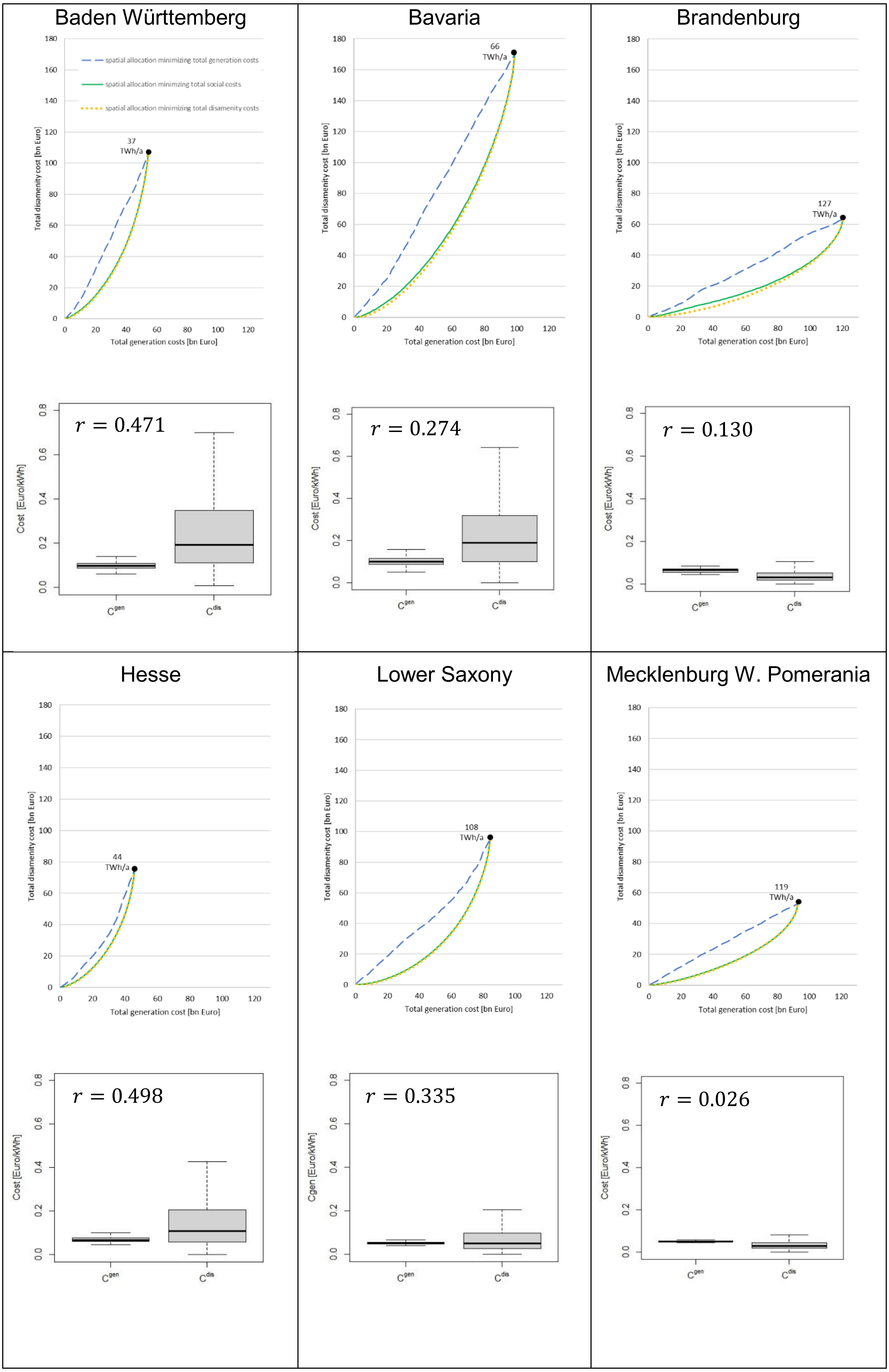
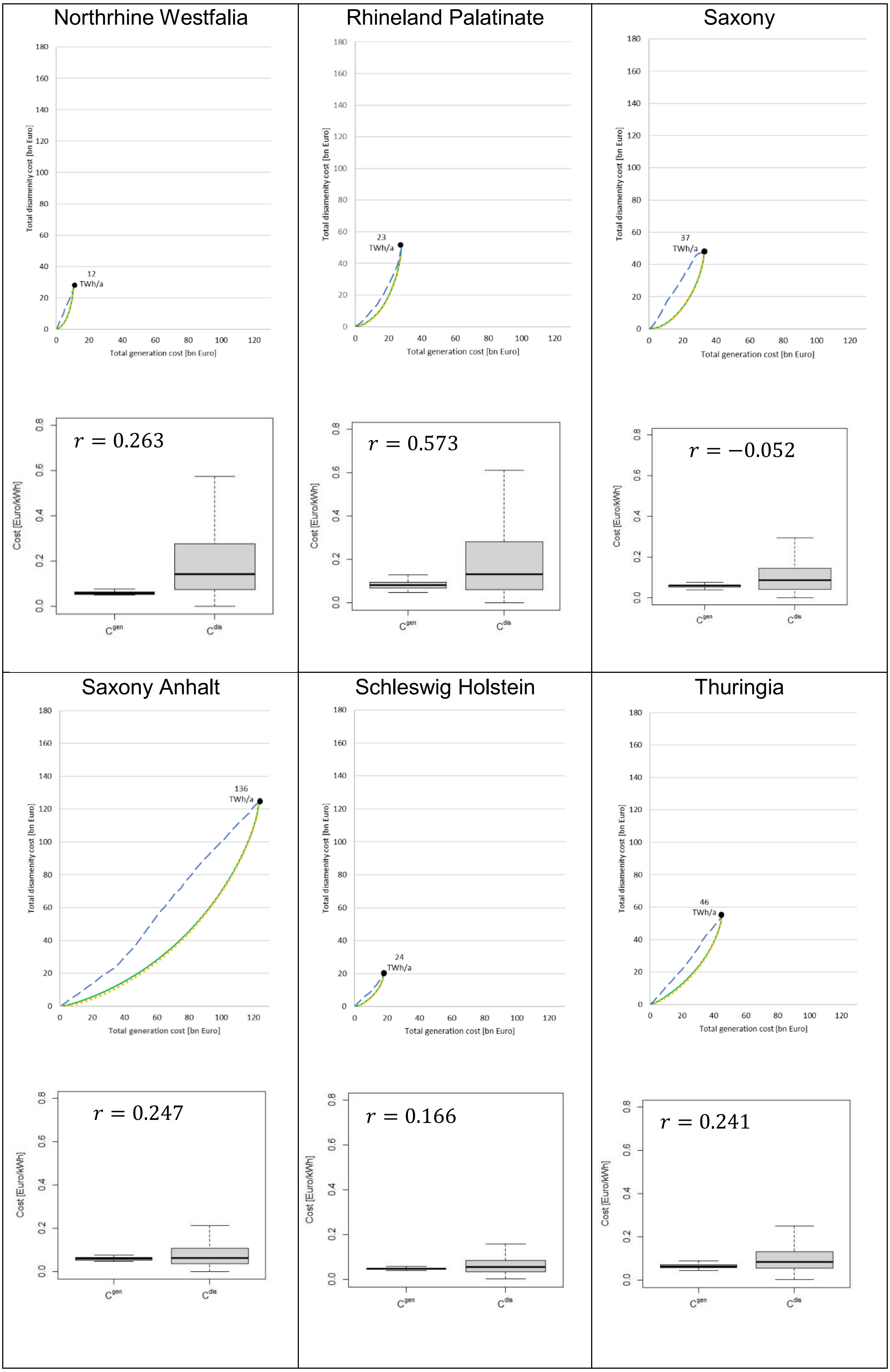


Figure 8: Optimization results for a) a high-linear disamenity cost function and b) low-linear disamenity cost function

3.2.2 Varying the geographic context

As the previous sensitivity analyses suggest, our results may be largely driven by the spatial heterogeneity in disamenity costs that results from the specific characteristics of settlement structure and distribution of population in our case study area, Germany. To assess the role of the specificity of the geographical context, we also carry out separate optimization runs for wind power deployment in the smaller spatial units of Germany’s states. Germany’s states exhibit at least some variation in the spatial patterns of settlement structure and population density allowing us to check how relevant such structural spatial differences may be for our findings.


Baden Württemberg
spatial allocation minimizing total generation costs
spatial allocation minimizing total social costs
spatial allocation minimizing total disamenity costs
37 TWh/a
Total disamenity cost [bn Euro]
Total generation costs [bn Euro]
r = 0.471
Cost [Euro/kWh]
C^gen
C^dis
Bavaria
66 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.274
Cost [Euro/kWh]
C^gen
C^dis
Brandenburg
127 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.130
Cost [Euro/kWh]
C^gen
C^dis
Hesse
44 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.498
Cost [Euro/kWh]
C^gen
C^dis
Lower Saxony
108 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.335
Cgen [Euro/kWh]
C^gen
C^dis
Mecklenburg W. Pomerania
119 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.026
Cost [Euro/kWh]
C^gen
C^dis



Northrhine Westfalia
12 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.263
Cost [Euro/kWh]
C^{gen}
C^{dis}
Rhineland Palatinate
23 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.573
Cost [Euro/kWh]
C^{gen}
C^{dis}
Saxony
37 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = −0.052
Cost [Euro/kWh]
C^{gen}
C^{dis}
Saxony Anhalt
136 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.247
Cost [Euro/kWh]
C^{gen}
C^{dis}
Schleswig Holstein
24 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.166
Cost [Euro/kWh]
C^{gen}
C^{dis}
Thuringia
46 TWh/a
Total disamenity cost [bn Euro]
Total generation cost [bn Euro]
r = 0.241
Cost [Euro/kWh]
C^{gen}
C^{dis}

Figure 9: Optimization results, box plots, and Pearson's correlation coefficients *r* of specific generation and disamenity costs across all potential sites for Germany's states (excluding the small territories of Berlin, Bremen, Hamburg, and Saarland)

Figure 9 illustrates differences between Germany's states. Naturally, the general extensions of the curves vary between the states due to differences in the number of potential sites, and thus the potential maximum deployment of wind power. States with relatively many potential sites (e.g., Bavaria, Mecklenburg Western Pomerania, or Saxony Anhalt, see also Table 1) will typically have higher total generation and total disamenity costs if all sites are used (upper right point of the curves) than states with relatively few sites only (e.g., Northrhine Westfalia, Rhineland Palatinate, or Schleswig Holstein). Curves are flatter – i.e., total disamenity costs increase only slowly with increasing generation targets – if specific disamenity costs are relatively low compared to specific generation costs (e.g., in Mecklenburg Western Pomerania or Brandenburg, see the respective box plots in Figure 9).

For all states, there is a substantial gap between the dashed blue curve (depicting the spatial allocation minimizing total generation costs for increasing generation targets) and the dotted yellow curve (depicting the spatial allocation minimizing total disamenity costs for increasing generation targets). This gap illustrates that the spatial trade-off between minimizing total generation and total disamenity costs also matters at the observed smaller spatial scale for all examined German states. Yet, Figure 9 also illustrates differences in the size of the trade-off across states. As one would expect, states with a relatively weak positive correlation between disamenity costs and generation costs (e.g., Brandenburg, Mecklenburg Western Pomerania, and Saxony Anhalt with a Pearson's correlation coefficient smaller than 0.1) exhibit comparatively large trade-offs. The reverse is true for states with a relatively strong positive spatial correlation between both variables (e.g., Hesse and Rhineland Palatinate with a Pearson's correlation coefficient of 0.5 and larger).

Moreover, the solid green curve more or less overlaps with the dotted yellow curve in all cases. This indicates that the socially optimal spatial allocation of wind power is dominated by disamenity costs also in all examined states. This can be explained by the fact that even in states with a relatively small spread in specific disamenity costs (e.g., Brandenburg and Mecklenburg Western Pomerania, see box plots in Figure 9), this spread is still clearly larger than the respective spread in specific generation costs that results from differences in local wind conditions. As the box plots in Figure 9 show, the differences of the spreads concern not only the extreme values of the respective costs (indicated by the whiskers) but also the majority of the respective cost values (indicated by the box sizes).

Therefore, properly considering the spatial heterogeneity in disamenity costs is key for deriving a socially optimal spatial allocation of wind power deployment in all German states.

Consequently, the results we obtained for Germany as a whole also seem to apply to all Germany's states individually, despite some differences in their geographic characteristics.

4. Discussion

Overall, our study provides evidence that the consideration of local disamenity costs may substantially alter the socially optimal spatial allocation of wind power deployment, compared to an optimization that only considers generation costs. Our analysis goes beyond the previous analyses by Drechsler et al. (2017; 2011) and Salomon et al. (2020) which also integrate disamenity costs into the spatial analysis of wind power deployment in Germany. These studies determine socially optimal uniform minimum distances between wind turbines and human settlements to address disamenity costs. With this approach, however, they only implicitly assess how disamenity costs shape socially optimal allocations: The more disamenities matter, the larger the socially optimal minimum distances will be. Drechsler et al. (2017) find that minimum distances should be as small as possible. This suggests that disamenity costs may not be decisive for a socially optimal allocation of wind turbines. In contrast, Drechsler et al. (2011) and Salomon et al. (2020) show that positive minimum distances may reduce the social costs of wind power deployment. Yet, these approaches likely underestimate the actual importance of disamenity costs for socially optimal wind power deployment because uniform minimum distances are a fairly costly means to internalize local disamenities. They do not allow to account for site-specific differences in both generation and disamenity costs. Our analysis uses an unconstrained optimization approach and thus provides a more precise assessment of how disamenity costs affect the socially optimal spatial allocation of wind turbines in Germany. It is therefore perfectly plausible that disamenity costs are more decisive in our model than in previous studies analyzing optimal minimum distances between wind turbines and settlements.

The observation that disamenity costs are key for identifying a socially optimal allocation of wind power deployment confirms the findings made by Grimsrud et al. (2021) for Norway. However, they argue that their result is primarily driven by the local disamenities that are caused by the grid extensions necessary to accommodate more wind power generation in the power system. Hence, wind turbines are reallocated from the windiest sites in their model to reduce the need for grid extensions and the respective local disamenities. In contrast, in our analysis (which ignores the social costs of grid extensions), disamenity costs drive the socially optimal allocation because their spatial heterogeneity is significantly larger than the spatial spread in generation costs. This effect is not fully captured in Grimsrud et al.'s model. They assume that all households within the municipality are equally affected by a wind turbine installed in that municipality. Thus, they do not consider the specific distances between a wind turbine site and the affected households. Since Grimsrud et al. (2021) do not fully account for the spatial heterogeneity in local disamenity costs, they might underestimate importance local disamenities for determining a socially optimal allocation of wind power deployment.

A variety of assumptions underlying our analysis certainly merit a critical discussion, particularly those regarding the assumed disamenity cost function.

The basic disamenity cost function. Our sensitivity analyses account for possible variations in the level and slope of the household-specific disamenity cost function c_h^{dis}. As pointed out, these variations may result from different methodologies to monetize local disamenities as well as different assumptions regarding habituation effects and discount rates. However, we do not alter our assumption that local disamenity costs are irrelevant if the distance between a wind turbine and a household exceeds 4,000 m. This assumption corresponds to empirical findings by Gibbons (2015) and Krekel and Zerrahn (2017). Yet, Sunak and Madlener (2017) find that disamenity costs already vanish at a slightly lower distance of 3,000 m. However, wind turbines may also impair households at far larger distances, for example, if turbines are installed highly visible on mountain ranges. Frondel et al. (2019) find, for example, that negative effects of wind turbines on house prices only fade to zero at a distance of 8,000 to 9,000 m. Modifying the actual cut-off value for the local disamenity cost function could thus either weaken or strengthen the relevance of local disamenities for a socially optimal wind turbine allocation.

Spatial heterogeneity. Our study is also limited by the fact that we only partly account for the spatial heterogeneity of disamenity costs. We do account for spatial heterogeneity determined by the distance to settlements and the size of population affected by a wind turbine. However, we assume that household-specific disamenity costs c_h^{dis} are only a function of the distance between a wind turbine and a household, i.e., homogenous across households for a given distance. This, of course, oversimplifies the empirical problem. For instance, spatial heterogeneity is also driven by locally specific geographical patterns. For example, disamenity costs depend on the visibility of wind turbines. Visibility is not only a function of distance but also of landscape patterns and relief (Gibbons, 2015; Jones and Eiser, 2010; Sunak and Madlener, 2016, 2017). Similarly, existing disamenities from other existing infrastructure (roads, industrial facilities) may determine how strongly residents are affected by wind turbines. Moreover, an extensive strand of literature shows that the valuation of disamenities may also vary across households depending on their individual attitudes, local social norms, or the degree of procedural and financial participation in siting decisions (e.g., Boyle et al., 2019; Brennan and van Rensburg, 2016; Knoefel et al., 2018; Liebe et al., 2017; Lienhoop, 2018; Mariel et al., 2015). Finally, the actual type of wind turbines installed – and thus the corresponding disamenity – may vary across sites, e.g., due to differences in windiness. Different heights and rotor diameters of installed wind turbines might also need to be reflected by site-specific disamenity costs functions (e.g., Brennan and van Rensburg, 2016). The effect of these neglected components of spatial heterogeneous disamenities on the optimal spatial allocation is hard to assess ex ante. This is due to the fact that the different components may partially aggregate or cancel out.

Cumulative effects. We further assume that disamenities produced by a wind turbine at a specific site are independent of how many wind turbines are installed in its vicinity. This assumption is not implausible as many studies find a linear relationship between the disamenity produced by a wind farm and the number of wind turbines (e.g., Brennan and van Rensburg, 2016; Mariel et al., 2015; Meyerhoff, 2013; Oehlmann and Meyerhoff, 2017). However, some studies also show that the disamenity costs produced by a wind farm may increase at a decreasing rate with the number of wind turbines, indicating negative cumulative effects (Betakova et al., 2015; Navrud and Braten, 2007). If negative cumulative effects are considered, the optimal spatial allocation will become more clustered in sparsely populated areas, where they produce low disamenity costs. Eventually, disamenity costs may thus be assumed to matter even more for the spatially optimal allocation with negative cumulative effects.

Geographic context. At first sight, the basic trade-off between minimizing total generation and total disamenity costs may be specific to the German geographic context. Considering disamenity costs substantially alters, and even dominates, the socially optimal optimal spatial allocation of wind power deployment in our analysis because 1) windy and sparsely populated sites do widely not coincide, and 2) the spatial heterogeneity is higher for disamenity costs than for generation costs in Germany. Disamenity costs may dominate the optimal spatial allocation of wind power deployment to a smaller extent or not at all in other geographic contexts if generation and disamenity costs are more positively correlated in space, or if spatial heterogeneity is lower for disamenity costs than for generation costs. This notwithstanding, there is some evidence that the spatial trade-off between minimizing total generation and total disamenity costs may be similarly prominent in other geographical contexts as well, e.g., the United Kingdom (McKenna et al., 2021).

Additional, spatially relevant costs. Our analysis of social costs of onshore wind power deployment focusses on generation and local disamenity costs produced by wind turbines. Obviously, considering additional components of the energy infrastructure (other generation technologies, grids) and corresponding types of costs may also be decisive for the socially optimal spatial allocation of wind turbines in a more holistic sense. System integration costs imply that siting decisions for wind turbines should consider network constraints or balancing requirements. This may significantly affect the optimal spatial allocation of wind power deployment, as has been show, for example, for Germany (Agora Energiewende, 2013; Bucksteeg, 2019; Drechsler et al., 2017). Moreover, the study by Grimsrud et al. (2021)

highlights that considering disamenity costs of complementary infrastructure may also alter the optimal spatial allocation of wind power deployment. In addition, ecological external costs, e.g., due to adverse effects of wind turbines on bird and bat populations, require wind turbines to be installed away from the habitats of affected species (Drechsler et al., 2011; Salomon et al., 2020; Schaub, 2012). Yet, while the inclusion of these costs may lead to a different socially optimal spatial allocation, they do not question the general relevance of local disamenities for choosing optimal sites for wind turbines.

5. Conclusion

The deployment of onshore wind power is an important means to mitigate climate change. However, wind turbines also produce local disamenties to residents living next to them. Our analysis shows that considerable spatial trade-offs materialize between allocations that minimize total generation costs and allocations that minimize total disamenity costs. Moreover, we find that the consideration of disamenity costs substantially alters – and in fact dominates – the socially optimal spatial allocation of wind power deployment. These results are robust to variations in the level and slope of the disamenity cost function assumed for our analysis.

Our results also have policy implications. They suggest that governance mechanisms allocating wind power deployment in space primarily on the basis of minimum generation costs – such as spatially uniform feed-in tariffs or tenders for renewable energies – most likely do not lead to a socially optimal outcome. This is not to say that support schemes should necessarily be readjusted to account for local disamenity costs. Instead, complementary policies may be used to account for the costs of local disamenities. Such policies may include compensation payments to households affected by wind turbines or (moderate) minimum settlement distances (Salomon et al., 2020). Yet, it is important to highlight that implementing a spatial allocation that considers disamenity costs does not by definition lead to a higher acceptance of wind turbines. In fact, studies show that acceptance is a complex function of exposure to wind turbines, personal attitude, social norms as well as procedural and financial participation in wind power siting decisions (e.g., Boyle et al., 2019; Devine-Wright, 2005; Knoefel et al., 2018; Liebe et al., 2017).

Three avenues for future research may be promising. First, the empirical foundation of the disamenity cost function used in the spatial optimization model can be further improved. Worthwhile extensions include a better representation of spatial heterogeneity in household-specific disamenities as well as of possible negative cumulative effects. Also, comparative studies may be helpful to better understand how different spatial contexts affect the relevance of disamenity costs for optimization. Second, an advanced model should also account for a broader set of renewable energy technologies and grid infrastructure. Other technologies, like solar photovoltaics or transmission lines, may exhibit different levels and patterns of local disamenities. An extended model could therefore allow analyzing how an optimal spatial allocation and an optimal technology mix might look like in the presence of a wider range local disamenities. For this purpose, the spatial optimization model could be coupled with a more complex electricity market and/or energy system model. This would additionally allow investigating spatial trade-offs between minimizing disamenity costs and a broader set of energy system costs (Grimsrud et al., 2021 provide a starting point).

References

Agora Energiewende, 2013. Kostenoptimaler Ausbau der Erneuerbaren Energien in Deutschland - Ein Vergleich möglicher Strategien für den Ausbau von Wind- und Solarenergie in Deutschland bis 2033. Agora Energiewende, Berlin.

Agora Energiewende, 2020. Klimaneutrales Deutschland - In drei Schritten zu null Treibhausgasen bis 2050 über ein Zwischenziel von -65 % im Jahr 2030 als Teil des EU-Green-Deals. Agora Energiewende, Berlin.

Agora Energiewende, Agora Verkehrswende, Stiftung Klimaneutralität, 2020. Towards a Climate-Neutral GermanyThree Steps for Achieving Climate Neutrality by 2050 and an Intermediate Target of -65% in 2030 as Part of the EU Green Deal. Agora Energiewende, Agora Verkehrswende, Stiftung Klimaneutralität, Berlin.

Baban, S., Parry, T., 2001. Developing and applying a GIS-assisted approach to locating wind farms in the UK. Renewable Energy 24, 59-71.

Betakova, V., Vojar, J., Sklenicka, P., 2015. Wind turbines location: How many and how far? Applied Energy 151, 23-31.

Boyle, K.J., Boatwright, J., Brahma, S., Xu, W., 2019. NIMBY, not, in siting community wind farms. Resour. Energy Econ. 57, 85-100.

Brennan, N., van Rensburg, T.M., 2016. Wind farm externalities and public preferences for community consultation in Ireland: a discrete choice experiments approach. Energ. Policy 94, 355-365.

Bucksteeg, M., 2019. Modelling the impact of geographical diversification of wind turbines on the required firm capacity in Germany. Applied Energy 235, 1476-1491.

Devine-Wright, P., 2005. Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. Wind Energy 8, 125-139.

Drechsler, M., Egerer, J., Lange, M., Masurowski, F., Meyerhoff, J., Oehlmann, M., 2017. Effcient and equitable spatial allocation of renewable power plants at the country scale. Nature Energy 2, 17124.

Drechsler, M., Ohl, C., Meyerhoff, J., Eichhorn, M., Monsees, J., 2011. Combining spatial modeling and choice experiments for the optimal spatial allocation of wind turbines. Energ. Policy 39, 3845-3854.

Dröes, M.I., Koster, H.R.A., 2016. Renewable Energy and Negative Externalities: The Effect of Wind Turbines on House Prices. Journal of Urban Economics 96, 121-141.

Dröes, M.I., Koster, H.R.A., 2021. Wind turbines, solar farms, and house prices. Energ. Policy 155, 112327.

DWD, G.M.S., 2014. Satzbeschreibung für digitale Weibulldaten (Skalen- und Formparameter), in: Service, G.M. (Ed.), Offenbach.

Ecer, F., 2021. Sustainability assessment of existing onshore wind plants in the context of triple bottom line: a best-worst method (BWM) based MCDM framework. Environmental Science and Pollution Research, https://doi.org/10.1007/s11356-11020-11940-11354.

Eichhorn, M., Masurowski, F., Becker, R., Thrän, D., 2019. Wind energy expansion scenarios - A spatial sustainability assessment. Energy 180, 367-375.

Eichhorn, M., Tafarte, P., Thrän, D., 2017. Towards energy landscapes - "Pathfinder for sustainable wind power locations". Energy 134, 611-621.

Enercon, 2015. ENERCON product overview, https://www.enercon.de/fileadmin/Redakteur/Medien-Portal/broschueren/pdf/en/ENERCON_Produkt_en_06_2015.pdf, p. 19.

Eriksen, E.H., Schwenk-Nebbe, L.J., Tranberg, B., Brown, T., Greiner, M., 2017. Optimal heterogeneity in a simplified highly renewable European electricity system. Energy 133, 913-928.

FA Wind, 2020. Überblick zu den Abstandsempfehlungen zur Ausweisung von Windenergiegebieten in den Bundesländern. Fachagentur Windenergie an Land (FA Wind), Berlin.

Fraunhofer ISE, 2021. Public Net Electricity Generation in Germany 2020: Share from Renewables Exceeds 50 percent. Fraunhofer ISE, Freiburg.

Frondel, M., Kussel, G., Sommer, S., Vance, C., 2019. Local Cost for Global Benefit: The Case of Wind Turbines, Ruhr Economic Papers #791. Ruhr-Universität Bochum, Rheinisch-Westfälisches Wirtschaftsforschungsinstitut (RWI), Bochum, Essen.

Fürsch, M., Hagspiel, S., Jägemann, C., Nagl, S., Lindenberger, D., Tröster, E., 2013. The role of grid extensions in a cost-efficient transformation of the European electricity system until 2050. Applied Energy 104, 642-652.

Gibbons, S., 2015. Gone with the wind: valuing the visual impact of wind turbines through house prices. J. Environ. Econ. Manage. 72, 177-196.

Gigović, L., Pamučar, D., Božanić, D., Ljubojević, S., 2017. Application of the GIS-DANP-MABAC multi-criteria model for selecting the location of wind farms: A case study of Vojvodina, Serbia. Renewable Energy 103, 501-521.

Grimsrud, K.M., Hagem, C., Lind, A., Lindhjem, H., 2021. Efficient spatial distribution of wind power plants given environmental externalities due to turbines and grids. Energ. Econ., https://doi.org/10.1016/j.eneco.2021.105487.

Guo, Y., Ru, P., Su, J., Diaz Anadon, L., 2015. Not in my backyard, but not far away from me: local acceptance of wind power in China. Energy 82, 722-733.

Hagspiel, S., Jägemann, C., Lindenberger, D., Brown, T., Cherevatskiy, S., Tröster, E., 2014. Cost-optimal power system extension under flow-based market coupling. Energy 66, 654-666.

Hanssen, F., May, R., van Dijk, R., 2018. Spatial Multi-Criteria Decision Analysis Tool Suite for Consensus-Based Siting of Renewable Energy Structures. Journal of Environmental Assessment Policy and Management 20, 1840003.

Heintzelmann, M.D., Tuttle, C.M., 2012. Values in the wind: a hedonic analysis of wind power facilities. Land Econ. 88, 561-588.

Hevia-Koch, P., Jacobsen, H.K., 2019. Comparing offshore and onshore wind development considering acceptance costs. Energ. Policy 125, 9-19.

Hirth, L., Müller, S., 2016. System-friendly wind power: How advanced wind turbine design can increase the economic value of electricity generated through wind power. Energ. Econ. 56, 51-63.

Höfer, T., Sunak, Y., Siddique, H., Madlener, R., 2017. Wind farm siting using a spatial Analytic Hierarchy Process approach: A case study of the Städteregion Aachen. Applied Energy 163, 222-243.

Janke, J.R., 2010. Multicriteria GIS modeling of wind and solar farms in Colorado. Renewable Energy 35, 2228-2234.

Jensen, C.U., Panduro, T.E., Lundhede, T.H., 2014. The vindication of Don Quixote: the impact of noise and visual pollution from wind turbines. Land Econ. 90, 668-682.

Johansson, V., Thorson, L., Goop, J., Göransson, L., Odenberger, M., Reichenberg, L., Taljegard, M., Johnsson, F., 2017. Value of wind power – Implications from specific power. Energy 126, 352-360.

Jones, C.R., Eiser, J.R., 2010. Understanding 'local' opposition to wind development in the UK: how big is a backyard? Energ. Policy 38.

Knoefel, J., Sagebiel, J., Yildiz, Ö., Müller, J.R., Rommel, J., 2018. A consumer perspective on corporate governance in the energy transition: Evidence from a Discrete Choice Experiment in Germany. Energ. Econ. 75, 440-448.

Kost, C., Shammugam, S., Juelich, V., Nguyen, H.-T., Schlegel, T., 2018. Levelized cost of electricity renewable energy technologies. Fraunhofer Institute for solar energy systems ISE, Freiburg.

Krekel, C., Zerrahn, A., 2017. Does the presence of wind turbines have externalities for people in their surroundings? Evidence from well-being data. J. Environ. Econ. Manage. 82, 221-238.

Ladenburg, J., Dubgaard, A., 2007. Willingness to pay for reduced visual disamenities from offshore wind farms in Denmark. Energ. Policy 35, 4059-4071.

Lang, C., Opaluch, J.J., Sfinarolakis, G., 2014. The windy city: property value impacts of wind turbines in an urban setting. Energ. Econ. 44, 413-421.

Lauf, T., Ek, K., Gawel, E., Lehmann, P., Söderholm, P., 2020. The regional heterogeneity of wind power deployment: an empirical investigation of land-use policies in Germany and Sweden. Journal of Environmental Planning and Management 63, 751-778.

Liebe, U., Bartczak, A., Meyerhoff, J., 2017. A turbine is not only a turbine: The role of social context and fairness characteristics for the local acceptance of wind power. Energ. Policy 107, 300-308.

Lienhoop, N., 2018. Acceptance of wind energy and the role of financial and procedural participation: An investigation with focus groups and choice experiments. Energy Policy 118, 97-105.

Mariel, P., Meyerhoff, J., Hess, S., 2015. Heterogeneous preferences toward landscape externalities of wind turbines – combining choices and attitudes in a hybrid model. Renewable and Sustainable Energy Reviews 41.

Masurowski, F., 2016. Eine deutschlandweite Potenzialanalyse für die Onshore-Windenergie mittels GIS einschließlich der Bewertung von Siedlungsdistanzenänderungen. University of Osnabrück.

Masurowski, F., Drechsler, M., Frank, K., 2016. A spatially explicit assessment of the wind energy potential in response to an increased distance between wind turbines and settlements in Germany. Energ. Policy 97, 343-350.

Mattmann, M., Logar, I., Brouwer, R., 2016. Wind power externalities: A meta-analysis. Ecol. Econ. 127, 23-36.

McKenna, R., Hollnaicher, S., Fichtner, W., 2014. Cost-potential curves for onshore wind energy: A high-resolution analysis for Germany. Applied Energy 115, 103-115.

McKenna, R., Weinand, J.M., Mulalic, I., Petrovic, S., Mainzer, K., Preis, T., Moat, H.S., 2021. Scenicness assessment of onshore wind sites with geotagged photographs and impacts on approval and cost-efficiency. Nature Energy, https://doi.org/10.1038/s41560-41021-00842-41565.

Meyerhoff, J., 2013. Do turbines in the vicinity of respondents' residences influence choices among programmes for future wind power generation? Journal of Choice Modelling 7, 58-71.

Meyerhoff, J., Ohl, C., Hartje, V., 2010. Landscape externalities from onshore wind power. Energ. Policy 38, 82-92.

Navrud, S., Braten, K.G., 2007. Consumers' Preferences for Green and Brown Electricity : a Choice Modelling Approach. Revue d'économie politique 117, 795-811.

Oehlmann, M., Meyerhoff, J., 2017. Stated preferences towards renewable energy alternatives in Germany – do the consequentiality of the survey and trust in institutions matter? Journal of Environmental Economics and Policy 6, 1-16.

Rodman, L.C., Meentemeyer, R.K., 2006. A geographic analysis of wind turbine placement in Northern California. Energ. Policy 34, 2137-2149.

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Séférian, R., Vilariño, M.V., 2018. Mitigation Pathways Compatible with 1.5° C in the Context of Sustainable Development, in: Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J.B.R., Chen, Y., Zhou, X., Gomis, M.I., Lonnoy, E., Maycock, T., Tignor, M., Waterfield, T. (Eds.), Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty in press.

Salomon, H., Drechsler, M., Reutter, F., 2020. Minimum distances for wind turbines: A robustness analysis of policies for a sustainable wind power deployment. Energ. Policy 140, 111431.

Sánchez-Lozano, J.M., García-Cascales, M.S., Lamata, M.T., 2016. GIS-based onshore wind farm site selection using Fuzzy Multi-Criteria Decision Making methods. Evaluating the case of Southeastern Spain. Applied Energy 171.

Schaber, K., Steinke, F., Hamacher, T., 2012a. Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? Energ. Policy 43, 123-135.

Schaber, K., Steinke, F., Mühlich, P., Hamacher, T., 2012b. Parametric study of variable renewable energy integration in Europe: Advantages and costs of transmission grid extensions. Energ. Policy 42, 498-508.

Schaub, M., 2012. Spatial distribution of wind turbines is crucial for the survival of red kite populations. Biological Conservation 155, 111-118.

Schlachtberger, D.P., Brown, T., Schramm, S., Greiner, M., 2017. The benefits of cooperation in a highly renewable European electricity network. Energy 134, 469-481.

Schmid, E., Knopf, B., 2015. Quantifying the long-term economic benefits of European electricity system integration. Energ. Policy 87, 260-269.

Sliz-Szkliniarz, B., Eberbach, J., Hoffmann, B., Fortin, M., 2019. Assessing the cost of onshore wind development scenarios: Modelling of spatial and temporal distribution of wind power for the case of Poland. Renewable and Sustainable Energy Reviews 109, 514-531.

Sunak, Y., Madlener, R., 2016. The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. Energ. Econ. 55, 79-91.

Sunak, Y., Madlener, R., 2017. The impact of wind farms on property values: A locally weighted hedonic pricing model. Papers in Regional Science 96, 423-444.

Tabassum-Abbasi, M.P., Abbasi, T., Abbasi, S.A., 2014. Wind energy: Increasing deployment, rising environmental concerns. Renewable and Sustainable Energy Reviews 31.

Tegou, L.-I., Polatidis, H., Haralambopoulos, D.A., 2010. Environmental management framework for wind farm siting: Methodology and case study. Journal of Environmental Management 91, 2134-2147.

von Moellendorff, C., Welsch, H., 2017. Measuring Renewable Energy Externalities: Evidence from Subjective Well-being Data. Land Econ. 93, 109-126.

Wallasch, A.-K., Lüers, S., Rehfeldt, K., 2015. Kostensituation der Windenergie an Land in Deutschland - Update. Deutsche Windguard, Varel.

Watson, J.J.W., Hudson, M.D., 2015. Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation. Landscape and Urban Planning 138, 20-31.

Wen, C., Dallimer, M., Carver, S., Ziv, G., 2018. Valuing the visual impact of wind farms: A calculus method for synthesizing choice experiments studies. Science of the Total Environment 637-638, 58-68.

Zerrahn, A., 2017. Wind Power and Externalities. Ecol. Econ. 141, 245-260.