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Quantifying trade-offs for the spatial allocation of onshore wind generation capacity – a case study for Germany

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Abstract:

The deployment of onshore wind power is an important means to mitigate climate change. However, wind turbines also have negative impacts at the local scale, like disamenities to residents living nearby, changes in landscape quality, or conflicts with nature conservation. Our paper analyses how these impacts affect the optimal siting of wind turbines, as compared to a spatial allocation focused solely on minimizing generation costs. To quantify the spatial trade-offs between these criteria, we propose a novel approach using Pareto frontiers and a Gini-like potential trade-off indicator. Our analysis builds on a spatial optimization model using geographical information system data for Germany. We show that spatial trade-offs between the criteria under consideration are significant. The size of the trade-off varies substantially with the criteria under consideration, depending on the spatial heterogeneity of each criterion as well as on the spatial correlation between the criteria. Spatial trade-offs are particularly pronounced between nature conservation (measured by impacts on wind power-sensitive birds) and other criteria.

Keywords: impact assessment; Germany; renewable energy; spatial optimization; wind power

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

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1. Introduction

Recent decades have witnessed a rapid expansion of new renewable energy sources like wind and solar photovoltaics on a global scale as a means to combat climate change and the depletion of natural resources (Rogelj, Shindell et al. 2018). As a consequence, the decisive question of how to allocate the expanding renewable generation capacities across space has emerged. Especially onshore wind power faces the challenge of adequate siting to mitigate possible negative impacts on diverse criteria. Relevant criteria for the allocation of onshore wind power (Mattmann, Logar et al. 2016) can range from well-established criteria like generation costs to impacts associated with disamenities for local residents, the aesthetic quality of the landscape and local nature conservation and species protection.

Often these criteria are heterogeneously distributed in space, so that the derived optimal allocation with respect to each of these criteria will likely differ depending on the selected criteria (Drechsler, Egerer et al. 2017, Eichhorn, Masurowski et al. 2019, Gauglitz, Schicketanz et al. 2019). As a consequence, there might exist trade-offs among the diverse allocation criteria so that minimizing the cost by an optimal allocation for one criterion might result in higher costs for another criterion. The understanding of trade-offs between different criteria for the optimal allocation of onshore wind power is still not widely covered in the literature. Similarly, how trade-offs develop and change with an increasing expansion of wind power remains largely unexplored. This lack of understanding of the potential trade-offs among different criteria is underlined by the fact that as yet no approach has been introduced to determine and quantify potential trade-offs.

Based on the described research gaps, we derived the following three research questions:

- First, we want to investigate if trade-offs between the most relevant criteria are significant for the allocation of onshore wind power.
- Second, we want to understand for which criteria spatial sustainability trade-offs matter most.
- Third, we want to answer how these trade-offs evolve with increasing levels of wind power deployment.

This paper will address these open questions and investigate how trade-offs in onshore wind power are present and evolving throughout the future expansion of wind power in Germany. This is will be performed for the trade-offs between four important criteria: generation costs, disamenities for residents, the aesthetic quality of the landscape, and nature conservation. Negative impacts with respect to these criteria will be referred to as costs in the remainder of this paper.

The spatial allocation of wind turbines can be optimized in order to minimize the costs connected to different criteria. Mono-criterial optimizations consider only a single criterion at a time. Thus they implicitly attach a weight of one to the criterion under consideration and a value of zero to all other criteria when optimizing the spatial allocation.

Many studies apply mono-criterial or multi-criterial optimizations for the allocation of wind turbines (Atici, Simsek et al. 2015, Drechsler, Egerer et al. 2017, Eichhorn, Tafarte et al. 2017, Eichhorn, Masurowski et al. 2019, Sasse and Trutnevyte 2019). The solutions of such mono-criterial optimizations often result in different optimal spatial allocation patterns given the heterogeneous distribution of the criteria in space, as many previous studies have demonstrated with respect to generation costs (Drechsler, Egerer et al. 2017, Eichhorn, Masurowski et al. 2019), nature conservation (Eichhorn, Tafarte et al. 2017, Eichhorn, Masurowski et al. 2019, Gauglitz, Schicketanz et al. 2019), regional equity (Sasse and Trutnevyte 2019, Neumann and Brown 2021) and disamenities for residents (Tafarte and Lehmann 2019, Salomon, Drechsler et al. 2020). Based on the heterogeneous distribution of the criteria in space which result in different optimal spatial allocations, it can therefore be concluded that trade-offs must exists among the compared criteria. The comparison of the resulting solutions of various mono-criterial optimizations can therefore provide a first impression on trade-offs (Eichhorn, Tafarte et al. 2017, Eichhorn, Masurowski et al. 2019, Sasse and Trutnevyte 2020).

Multi-criterial optimizations include multiple criteria simultaneously to solve the allocation problem, and there are consequently multiple weights attached to the criteria. When applying multi-criterial optimization to the allocation problem, the question of how to weight the different criteria thus arises. In such cases, equal weights are often attributed to the different criteria considered (Eichhorn and Drechsler 2010, Ohl and Eichhorn 2010, Schaber, Steinke et al. 2012, Agora Energiewende 2013, Fursch, Hagspiel et al. 2013, Hagspiel, Jagemann et al. 2014, Eichhorn, Tafarte et al. 2017, Eriksen, Schwenk-Nebbe et al. 2017, Schlachtberger, Brown et al. 2018, Bucksteeg 2019, Eichhorn, Masurowski et al. 2019), or qualified expert knowledge is used for the weighing of criteria (Ecer 2021). An additional problem can arise when criteria of different dimension cannot be converted into a common metric to be optimized simultaneously, like monetary cost for example. Consequently, multi-criterial optimization is dependent on the weights attributed to the different criteria, and in some cases it is challenged by criteria of different dimensions.

Overall, both mono- and multi-criterial optimizations have in common that they only provide discrete optima to the allocation problem. Consequently, the scope and magnitude of potential trade-offs remains unknown and no full coverage of feasible solutions throughout the entire expansion path is provided. Furthermore, there is little knowledge on how costs and potential trade-offs evolve with the expansion of wind power. To overcome this shortcoming, and to provide an overarching approach to determine the potential trade-offs for the allocation of wind turbines, we add to this research field by providing an approach to determine the entire feasible region, which entails all possible solutions and therefore also all trade-offs for the allocation problem.

In order to provide such a full coverage of potential trade-offs, a quantification of potential trade-offs can be performed using a Pareto optimization, which allows determining optimal solutions for a criterion in a paired comparison under set constraints for another criterion (Soroudi 2017). We use such Pareto frontiers to determine the feasible region for the allocation problem of expanding wind power generation. The feasible region is demarked by the calculated discrete Pareto optima which form a Pareto frontier in the paired comparison of two criteria. The feasible region entails all the potential solutions to the allocation problem. This way, instead of providing mono-criterial optima or any other predefined preference for one criterion over another in a multi-criterial approach, the full degree of freedom to choose possible solutions can be provided.

Based on the calculation of the feasible regions, we quantify the potential trade-offs among different criteria. Therefore, we adapt the concept of the Gini coefficient that can be derived from the Pareto frontiers in the paired comparison between two criteria which are interpreted as the Lorenz curve. In our case, the Lorenz curve allows us to calculate the dimensionless Gini-like potential trade-off indicator (PTI) that summarizes the magnitude of the potential trade-off between two criteria and enables us to quantify and compare trade-offs among different allocation criteria. Consequently, the calculated PTI does not focus on optimal solutions or finding spatial allocations, but rather on the determination and quantification of potential trade-offs among selected allocation criteria.

As a further mean to visualize the impact of the different criteria on the spatial allocation of onshore wind power, we provide a mapping of the selected wind turbines for the mono-criterial optima for a potential 2030 expansion target of 200 terawatt hours annually (TWh/a). This complements the results from the quantitative approach using the PTI and provides the spatial allocation patterns for different allocation criteria on the regional scale.

In section 2 we will describe the method applied in this paper. Section 3 will present the results, starting with the determination of the overall feasible region, trade-offs and the development of the costs of all four criteria over the entire expansion potential as well as for the 200 TWh/a expansion scenario. Section 4 discusses the presented results and places them in the context of the existing research in the field, while section 5 provides concluding remarks to the presented paper.

2. Methods and Modelling

In the methods section we first introduce the overall optimization approach and provide a description of the four criteria utilized in this study, before details on the study area and the investigated scenarios are provided.

2.1. Optimization approach

We perform two different optimizations. First, a bi-objective Pareto optimization is carried out to identify the overall feasible region to the allocation problem for all four criteria utilized in this study. The criteria are the electricity generation costs (C^{gen}), the disamenity costs for local residents (C^{dis}), the costs associated with the impacts on the aesthetic landscape quality (C^{land}), and the costs associated with the impacts on nature conservation (C^{nat}). These four criteria can be arranged in six separate paired comparisons. Secondly, we will calculate the four mono-criterial optimizations possible for the four different criteria with a set generation target (GT). Both optimization approaches are described below.

2.1.1. Pareto optimization

We use a bi-objective Pareto optimization to quantify potential trade-offs between two different allocation criteria. A key characteristic of the Pareto optimization is that it allows for multiple objectives to be followed. In contrast to solving mono-objective problems with only one optimum solution, the Pareto optimization can provide various optimal solutions to the allocation problem. The efficient solutions forming the Pareto frontier are so-called non-dominated solutions, meaning that within the set of feasible solutions there exists no solution which is superior in at least one of the two criteria to be optimized. Furthermore, we have chosen the Pareto optimization as it enables optimizing criteria of different dimensions, for example criteria quantified in monetary values like generation costs and disamenity costs, and non-monetary criteria like aesthetic landscape quality or nature conservation.

First we apply a bi-objective Pareto optimization in which the cumulated costs for one criterion are subject to optimization while we apply constraints to the cumulated costs for the second criterion, which cover the entire range of values from zero to the maximum cumulated cost for the second criterion, described by Soroudi (Soroudi 2017) and Chircop et al. (Chircop and Zammit-Mangion 2013) as the equidistant Ɛ-constraint method. For the description and implementation of the bi-objective Pareto optimization into GAMS, we refer to these two references and another application of the Ɛ-constraint method performed in a paper by Neumann and Brown (Neumann and Brown 2021).

The stepwise, equidistant Ɛ-constraint optimization is conducted both as a minimization and as a maximization for either of the two criteria in the paired comparison. Consequently, two Pareto frontiers result from the optimization: an upper Pareto frontier marking the non-dominated solutions for the maximum cumulated cost, and a lower Pareto frontier for the minimum cumulated cost. The two Pareto frontiers create an envelope around all feasible solutions, the feasible region for the allocation (Chircop and Zammit-Mangion 2013). The feasible region entails all the solutions for two criteria covering the expansion of wind power production from zero to full expansion potential in a paired comparison (Figure 1). Possible trade-offs among the criteria are accordingly also limited to the feasible region.

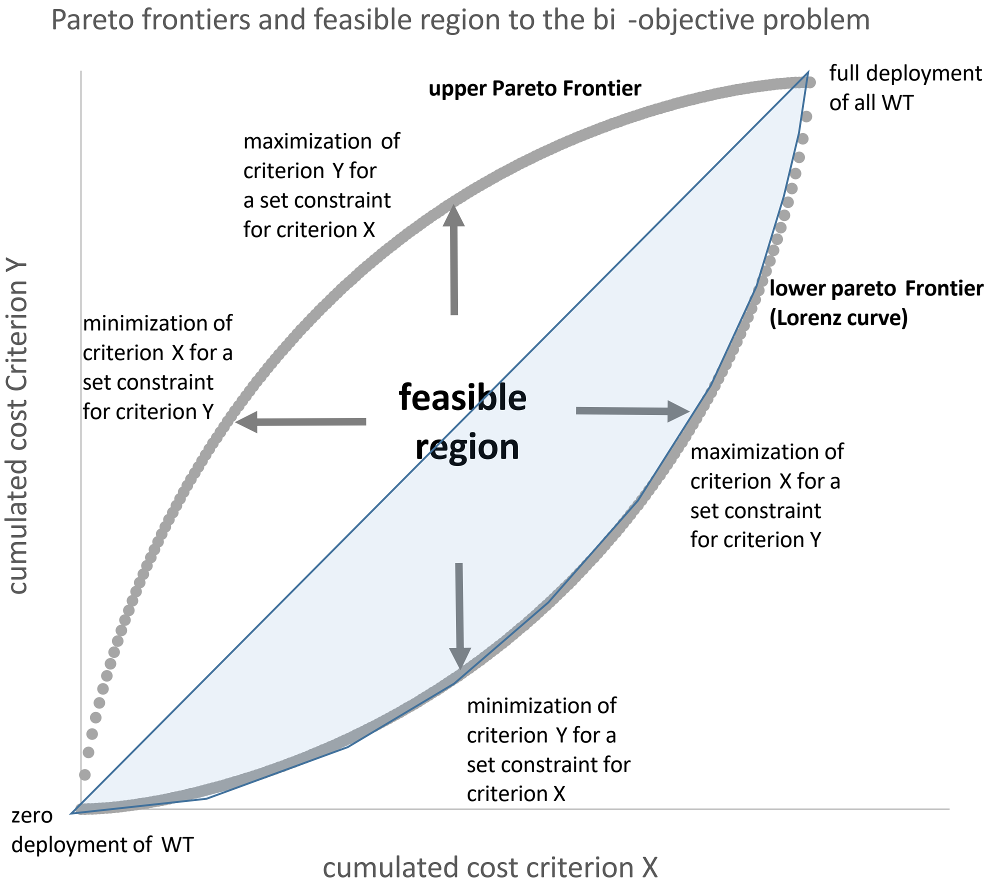


Figure 1: Determination of the feasible region by two Pareto frontiers using constrained optimization between criterion X and criterion Y; lower Pareto frontier interpreted as the Lorenz curve and the enclosed area A and B to derive the PTI.

If the calculated Pareto frontiers were identical to the hypothetical straight line, all wind turbines would have a constant relation of costs with regard to the two compared criteria. This would also require that the criteria of all wind turbines are perfectly positively correlated (the correlation coefficient R for all paired comparisons is therefore provided in the figures in the results section).

In general, the feasible region first increases with the expansion of allocated wind turbines due to the increasing degree of freedom for the allocation and the possibility to allocate cost-minimal or cost-maximal wind turbines up to a point where trade-offs reach a maximum. Afterwards, the feasible region decreases towards the full deployment of all wind turbines, at which point the maximum cumulated costs are located for both cost criteria and where ultimately no degree of freedom remains.

The two Pareto frontiers are point symmetrical, with the centre of symmetry lying on the straight line connecting the origin of the graph and the full deployment of all wind turbines. This is due to the fact that the potential wind turbines selected are ordered according to the specific cost relation of criteria X and Y. Depending on whether minimal cumulative costs or maximum cumulative costs are targeted by the optimization, the respective wind turbines are selected in ascending or descending order.

2.1.2. Potential trade-off indicator (PTI)

In order to quantify the feasible region and therefore also the potential trade-off in a paired comparison, we interpret the lower Pareto frontier as a Lorenz curve for the distribution of the cumulated costs of one criterion to the cumulative costs of the other criterion. The Lorenz curve is constructed by plotting the cumulative costs of one criterion over the ascending cumulative costs of the other criterion It is therefore the graphical representation of the disproportionality in the distribution between two criteria and can be quantified in size by the Gini coefficient, as demonstrated also by Neumann and Brown (Neumann and Brown 2021) as well as by Sasse and Trutnevyte (Sasse and Trutnevyte 2019).

The lower Pareto frontier or Lorenz curve can now be compared to a hypothetical straight line connecting the origin of the graph at zero deployment of wind turbines up to the maximum expansion allocating all potential wind turbines. If the calculated lower Pareto frontier was identical to the hypothetical straight line, all wind turbines would have a constant relation of costs with regard to the two compared criteria. In this case, the allocation problem would be trivial as no wind turbine would be superior to any other with regard to the two criteria and thus no trade-offs between the two criteria would be possible. Consequentially, we can then quantify the potential trade-off through a trade-off coefficient (PTI), analogously to the Gini coefficient. It is calculated as the ratio of the enclosed area between the lower Pareto frontier and the hypothetical straight line (area A in Figure 1) on the one hand side and the triangular below the hypothetical straight line on the other (area A+B in Figure 1). Based on the Lorenz curve, we calculate a dimensionless PTI. In our case this is approximated numerically in discrete steps using the following formula:

$$PTI = \quad 0{,}5 * Xn * Yn * \sum_{k=1}^{n} \; (X_k - X_{k-1}) * (\frac{k}{n} * Yn - Y_k) \qquad (1)$$

k is the index of the calculated Pareto optima in the Pareto frontier used for n steps of the calculation of the enclosed area, X and Y the cumulated cost of the two different criteria of the paired comparison.

Generally, the greater the area of the feasible region enclosed, the higher the potential trade-off, and accordingly the greater the PTI between the two compared criteria. Like the Gini coefficient, the PTI ranges between 0 and 1. A value of 0 (case of the straight line) implies that trade-offs are absent. A value of 1 indicates the maximum potential trade-off.

This approach for determining the potential trade-offs refers to the overall allocation problem over the entire possible expansion path for two criteria. To determine the specific trade-off between two criteria, the feasible region needs to be restricted to a specific generation target, as outlined in the following.

2.1.3. Pareto optimization with an annual generation target of 200 TWh set as a constraint

We set a generation target (GT) as a constraint for the calculation of the specific Pareto frontiers and the feasible region.

$$GT = \sum_{i=1}^{n} \mathrm{AEP}_i * \mathrm{WT}_i \tag{2}$$

i denominates the index of n potential wind turbine (WT), AEP_i is the annual energy production of potential wind turbine WTi and GT is the generation target of, in our case, 200 TWh/a.

This specific feasible region for a given GT is a subset of the feasible region and consequentially falls within the boundaries of the latter. Such a specific feasible region can serve as a useful decision element for a case-specific task in comparison to the feasible region and potential trade-off indicator, which applies to the overall allocation problem in a paired comparison as stated.

2.1.4. Mono-criterial optimization with an annual generation target of 200 TWh

A mono-criterial optimization is provided for each of the four criteria in addition to the Pareto optimization described above. For the given generation target GT, we calculate mono-criterial optima for each of the criteria. These mono-criterial optimizations of all four criteria will allow for a basic comparison of trade-offs with a set generation target for onshore wind in Germany as well as the mapping of spatial patterns in the allocation (cref 3.3).

The four individual optimizations are:

$$\min_{WT_{i=1..n}} \sum_{i=1}^{n} C_i^{\text{gen}} * WT_i \tag{3}$$

$$\min_{WT_{i=1..n}} \sum_{i=1}^{n} C_i^{\text{dis}} * WT_i \tag{4}$$

$$\min_{WT_{i=1..n}} \sum_{i=1}^{n} C_i^{\text{land}} * WT_i \tag{5}$$

$$\min_{WT_{i=1..n}} \sum_{i=1}^{n} C_i^{\text{nat}} * WT_i \tag{6}$$

i denominates the index of n potential wind turbine sites (WT), C_i^{gen} the generation costs, C_i^{dis} the disamenity costs, C_i^{land} the costs of landscape quality and C_i^{nat} the nature conservation costs. All equations are subject to the annual generation target GT of 200 TWh.

2.2. Data and calibration

2.2.1. Study region and potential sites

Germany is one of the pioneers of the large-scale introduction of modern wind energy and has ambitious plans for the energy transition based on wind and solar PV. It is one of the leading industrialized countries, with high overall energy consumption, and has also a high population density and stringent legal rules to safeguard residents as well as the environment and protected species. New infrastructure with a high spatial footprint, like most renewable energy sources (Brücher 2009, Luderer, Pehl et al. 2019), therefore always involves conflicts and potential trade-offs with regard to their spatial allocation. Germany was therefore chosen as a case study region to investigate the associated trade-offs connected to the expansion of future wind power generation capacity and its spatial allocation.

A GIS-based modelling to answer these questions first assesses the overall potential sites for onshore wind energy in Germany in a green field approach. A total of 106,497 spatially explicit potential sites (Figure 2) were identified on the basis of legal and technical restrictions (e.g. minimum distances to settlements and certain infrastructures, protected areas and areas technically unsuitable for the installation of wind turbines, e.g. due to excessive terrain slope). These data were derived from Masurowski (Masurowski 2016). Minimum distances to settlements were updated and extended to 600-800 meters, depending on legal status of the settlement, structure to comply with current (2019) noise emission protection regulations in Germany. Each of these identified sites fits a single wind turbine in the 3 MW class (Enercon E-101 3MW). These potential sites or potential wind turbines are attributed values of all four indicators for the criteria and form the empirical basis for the modelling.

Figure 2: Map showing all potential sites for wind turbines

For the overall analysis, we apply the described approach for the entire set of potential wind turbine sites in Germany. The cumulated annual energy production (AEP) of all 106,497 potential wind turbine sites amounts to 778 TWh/a, which is almost 10 times the energy provided by onshore wind power in Germany in 2017 (UBA 2018).

In addition to the overall potential trade-off analysis, we apply the identical approach to calculate potential trade-offs for a generation target of 200 TWh/a. This generation target can be regarded as an ambitious expansion scenario for onshore wind power in Germany for 2030 (Nitsch, Pregger et al. 2012, Agora Energiewende 2013), so that an application of the overall approach is exemplified for the medium term.

Impacts on criteria, or costs in economic terms, can entail monetary costs associated with the generation of wind power as well as non-monetary costs. In the following, the calibration of the four modelled criteria used for the optimization is described.

2.2.2. Criterion generation costs (C^{gen})

The commonly used monetary costs are the specific generation costs in terms of the levelized cost of electricity (LCOE) or system integration costs as an allocation criterion (Agora Energiewende 2013, Drechsler, Egerer et al. 2017, Tafarte and Lehmann 2019). Based on the power curve of the Enercon E101 3.0 MW wind turbine (Enercon 2015), high resolution wind climate data (DWD 2020) is used to calculate the annual energy production (AEP) for each potential site (Eichhorn, Tafarte et al. 2017). Losses in AEP have been accounted for by a uniform AEP reduction for each turbine by 15%. This covers for example the wind park effect, where wind turbines suffer losses due to the wake turbulences induced by the operation of other WT in close proximity, as well as downtimes for maintenance and repairs.

The AEP is used jointly with overall monetary costs for investment, installation as well as operation and maintenance (Anna-Kathrin Wallasch, Silke Lüers et al. 2015) of the wind turbine throughout the operational lifetime of 20 years to calculate the levelized cost of electricity (LCOE) in accordance with (Kost, Shammugam et al. 2018):

$$LCOE = \left(\frac{I_0 + \sum_{t=1}^{5} \frac{A_{1t}}{(1+r)^t} + \sum_{t=5}^{20} \frac{A_{2t}}{(1+r)^t}}{\sum_{t=1}^{20} \frac{AEP}{(1+r)^t}} \right) \tag{7}$$

I_0 is the investment expenditure in the first year of operation (1,567 EUR/kW). A_{1t} is the annual total cost per year t for the first 5 years of operation (30 EUR/kW), A_{2t} the annual total cost per year t for the remaining 15 years of operation (50 EUR/kW). AEP is the generated amount of electricity per year [kWh], r the discount rate at an annual rate of $r = 0.03$, n the economic lifetime in years, and $t = (1, 2, \ldots, 20)$ the year of lifetime. The utilized parameters are taken from Wallasch et al. (2015).

The generation costs are finally calculated as:

$$C_{gen} = 20 * \sum_{i=1}^{n} LCOE_i * AEP_i * WT_i \tag{8}$$

C_{gen} is the cumulated generation cost over 20 years, $LCOE$ the levelized cost of electricity, AEP the annual energy production and WT_i all the selected wind turbines i.

2.2.3. Criterion disamenity costs (C^{dis})

A detailed description of the overall estimation of disamenities for residents applied in this paper can be found in Salomon et al. (Salomon, Drechsler et al. 2020). The disamenity cost function calibrated and described by Salomon et al. reflects increasing marginal disamenity costs with decreasing household to turbine distances as they are typically observed in willingness-to-pay analyses (Wen, Dallimer et al. 2018). The shape of the used hyperbolic cost function is determined by drawing on different values found in the literature (Meyerhoff, Ohl et al. 2010, Gibbons 2015, Krekel and Zerrahn 2017). Several studies indicate that a wind turbine does not cause local disamenities for a resident if the distance of the turbine to the household is greater than about 4,000 m. Therefore, it is assumed that the hyperbolic cost function runs to zero at 4,000 m. Altogether, the aforementioned study values are cast into a hyperbolic function plotted in Figure 3.

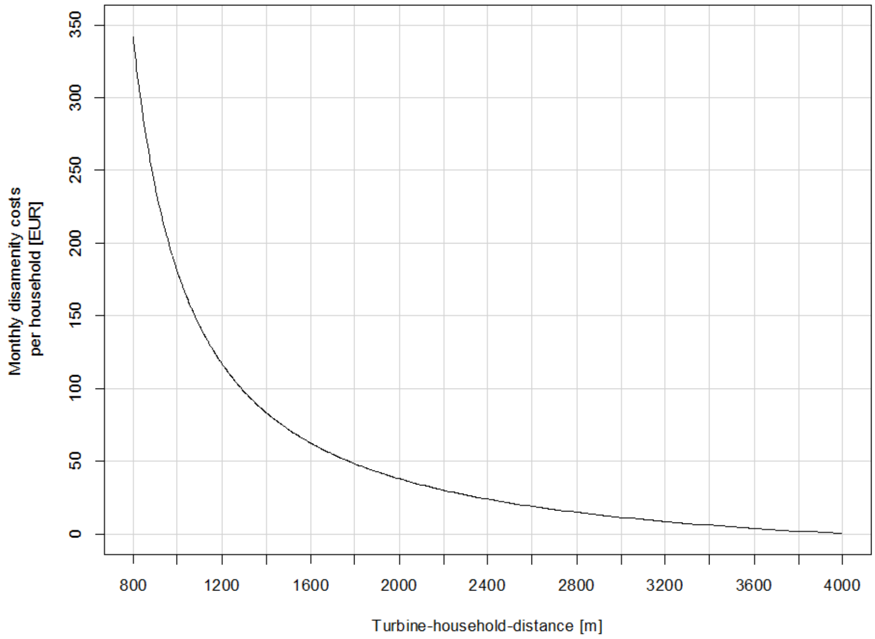


Figure 3: Assumed monthly disamenity costs c_{ih}^{dis} (in EUR) accruing to a household h from wind turbine i depending on the turbine-household distance d in meters [m] (Salomon, Drechsler et al. 2020)

Disamenity costs per household are discounted at an annual rate of $r = 0.03$ (see, e.g., Drechsler, Ohl et al. 2011) over a twenty-year time frame. Finally, the overall disamenity costs of a particular wind turbine allocation can then be calculated by adding up the single disamenity costs of all households within 4,000m of the potential wind turbine site.

In contrast to other modelling on disamenities for local residents and criteria which are developed to cover aspects of human well-being (Eichhorn, Tafarte et al. 2017, Eichhorn, Masurowski et al. 2019), the modelling applied here takes all settlement areas within a 4,000 m radius of the wind turbine into consideration, as well as the number of inhabitants of the respective settlements. The presented modelling is therefore more refined and should account for the actual disamenities with a higher accuracy than previous approaches.

2.2.4. Criterion aesthetic landscape quality (C^{land})

Modern wind turbines are especially prone to visual impacts due to their sheer size as well as their siting requirements on exposed localities. This can have a negative visual impact on the landscape, and such costs are likewise associated with the spatial allocation of wind turbines (Kienast, Huber et al. 2017, McKenna, Weinand et al. 2020). We use a spatially high-resolution and uniform assessment of the landscape aesthetics for Germany published by Hermes et al.

(Hermes, Albert et al. 2018). Here the aesthetic landscape quality has been ranked on a scale from 0 to 100 with a high resolution of 100 m x 100 m and is based on the attributes of diversity, naturalness and uniqueness of the landscape (compare also the German federal law for nature conservation (*Bundesnaturschutzgesetz*, BNatSchG §1 (1) 3). We now attribute every potential wind turbine based on the average of the neighbouring elements within a 1000 m radius. This modification was made to better aggregate the overall value of the surroundings of the wind turbine as well as to account for the fact that the effect of a modern wind turbine reaches much further than the original 100 m x 100 m radius. By minimizing the cost associated with the allocation of wind turbines, the optimization will give priority to the allocation of wind turbines to sites with a low aesthetic landscape quality.

2.2.5. Criterion nature conservation (C^{nat})

Although several areas of potential negative impact of wind turbines on nature and species conservation are currently being researched, in Germany the main focus of research and the most relevant aspect for the legal approval of wind turbines in practice is the impact on wind power-sensitive bird species. Accordingly, we have derived a cost proxy that is based on the abundance of bird species considered sensitive to wind turbines as well as on the recommended minimum distances of wind turbines to nesting sites of the respective bird species, as laid down by the "Helgolaender Papier" (LAG_VSW 2015, Schlacke and Schnittker 2015). The abundances are taken from the nationwide registration of the number of breeding pairs of the respective bird species, covering Germany on topographic maps with a spatial resolution of roughly 10,000 m x 10,000 m (ADEBAR Atlas).

We calculate the conflict indicator by applying the following formula:

$$c_r^{nat} = \sum_{i=1}^{n} \left(A_{i,r} * area_i\right) \tag{9}$$

c_r^{nat} is the proxy for the nature conservation costs in region *r*, A_i is the average abundance of the respective species *i* and $area_i$ is the normalized area for species *i* which is provided in table A1 in the appendix.

The number of breeding pairs per bird species is thus weighted by the normalized circular area and aggregated for all species in the region, resulting in a single aggregated cost proxy per region which is assigned to all wind turbines located in the respective region.

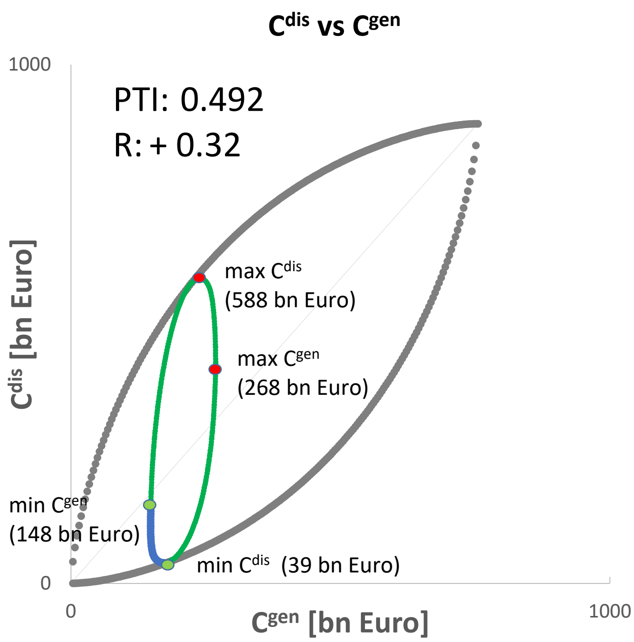
3. Results

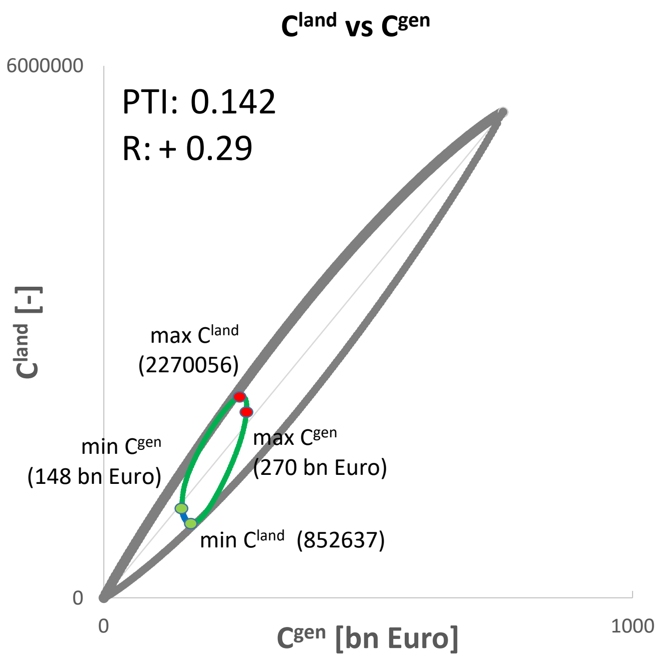
In the following, we provide the results of the potential trade-offs we identified by determining the potential feasible region for the paired comparison of the unconstraint case. Additionally, the constraint feasible region for a generation target of 200 TWh/a as well as a comparison of the resulting mono-criterial costs for all four criteria is presented. Maps of the spatial allocation of wind turbines in the 200 TWh/a scenario and the intersection of wind turbines (no-regret sites) in the different mono-criterial solutions are presented at the end of the results section.

3.1. Overall feasible region and potential trade-offs

In the paired comparisons of the criteria we determine the potential feasible region for the overall allocation problem. The feasible region is demarked by two separate Pareto frontiers which are determined by the cost-minimal and the cost-maximal solution for both criteria throughout the possible expansion of wind power production in Germany from 0 to 778 TWh/a.

Figure 4 below provides the six possible paired comparison in the form of the overall feasible region (grey-lined feasible region), the connected potential trade-off indicator (PTI) and the Pearson's correlation coefficient (R) (Frost 2020), which is calculated for all potential wind turbine sites of the respective criteria in the paired comparison.





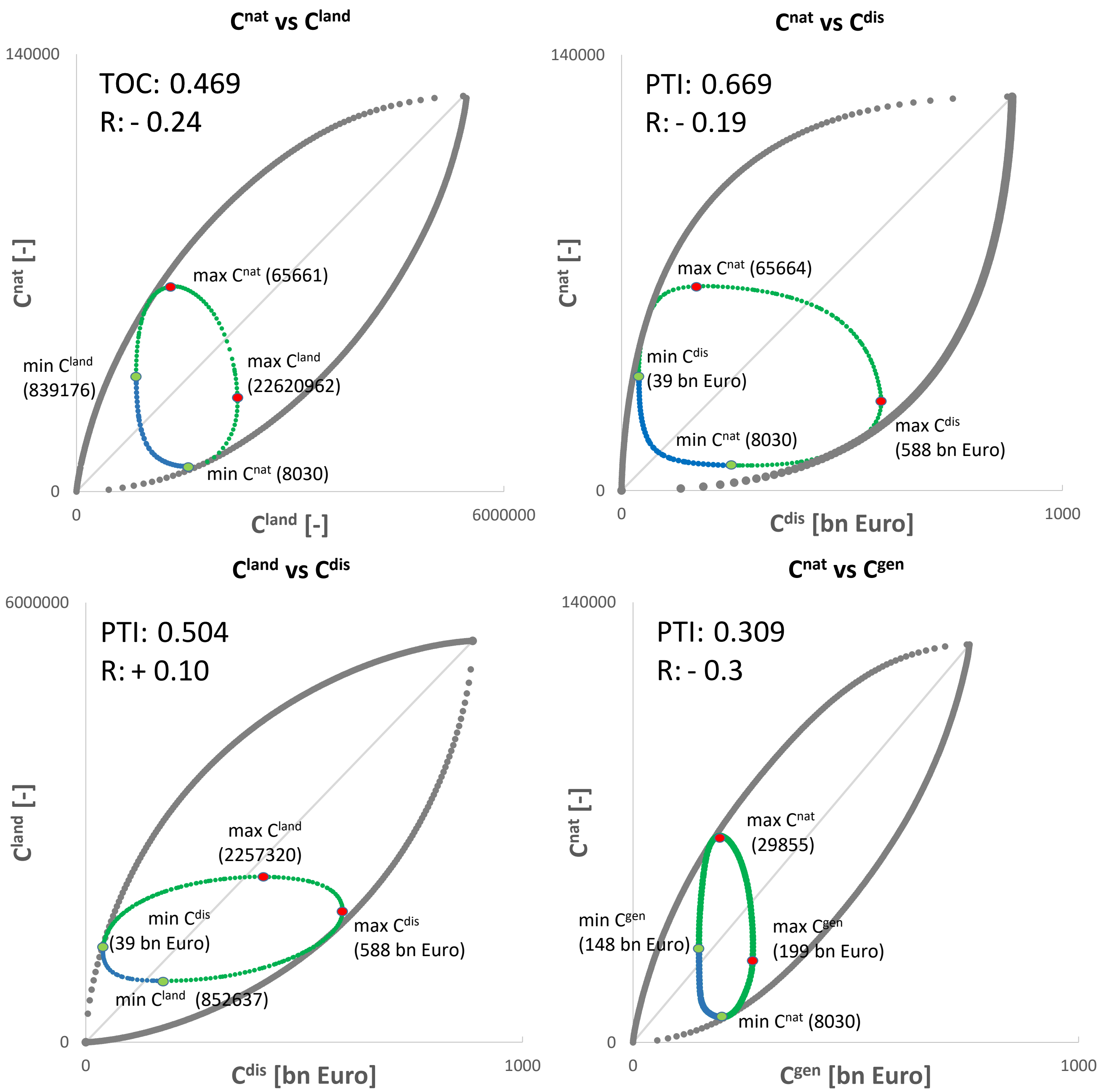


Figure 4: Pareto frontiers as boundaries for the overall feasible region (grey) and for the constrained 200 TWh/a generation target (green) including the efficient cost-minimal Pareto frontier (blue) with markings for the cost-minimal (green) and cost-maximal solutions (red). Additionally provided are the potential trade-off indicator (PTI) and the correlation coefficient for all six possible paired comparisons.

The overview across the six paired comparisons underlines that there various shapes of Pareto frontiers are observable. Accordingly, the cumulated costs and associated trade-offs vary significantly between the different criteria in the paired comparison and over the course of the possible wind energy expansion.

The most significant potential trade-off with the largest size of feasible region and accordingly also the largest PTI of 0.669 is observed between the C^{dis} and C^{nat}. Accordingly, lower C^{dis} can be traded to a large extent for higher C^{nat} and vice versa. In contrast, this is only possible to a minor extent for the paired comparison between C^{gen} and C^{land}, where the possible feasible region allows only minor room to trade one criterion for the other with the smallest feasible region and a PTI of only 0.142. All PTI of the four remaining paired comparisons range between with values of 0.469 to 0.504.

As an explanation for these observed and quantified differences in the size of the feasible region and therefore the PTI, we identified two characteristics of the costs under consideration: a) their spatial variability, and b) their spatial correlation.

The spatial variability of the four criteria themselves is one characteristic that causes the differences in PTI. Variability of at least one criterion is a necessary condition for trade-offs as two invariant criteria do not allow for any differences in the cost optimization and consequentially make trade-offs impossible. A high variability is observed for the criteria C^{nat} and C^{dis}. C^{gen} and C^{land} in contrast have a lower variation coefficient (Figure 5).

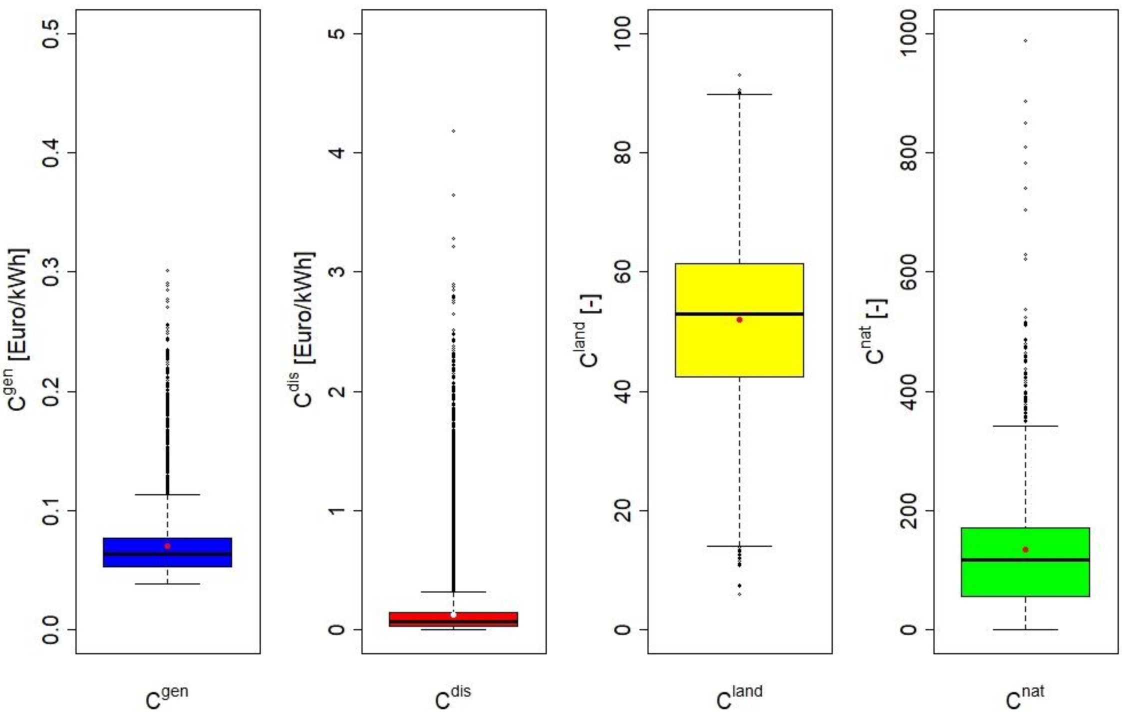


Figure 5: Descriptive statistics presented as box-whisker plots for all four criteria.

b) The other necessary characteristic which determines the PTI is the correlation between the two criteria in a paired comparison. The paired comparison is performed for two criteria at the same locality of the potential wind turbine over the entire set of 106,497 potential sites. The resulting correlation is likewise a spatial correlation of the respective criteria and is therefore likewise linked to the modelled spatial patterns of the criteria, such as C^{gen} as a function of wind speeds generally decreasing from north to south in Germany or C^{dis} as a function of population density and settlement structures connected to urban and rural regions across the study area. The PTI is also dependent on the differences in the spatial correlation of the criteria, as indicated by the correlation coefficient R for the paired comparisons provided in Figure 4. A positive correlation indicates that the associated cost over all wind turbine sites for one criterion is statistically related to an increased cost for the other criterion. A negative correlation indicates an inverse relationship. For the investigated trade-offs, this implies that potential trade-offs have a tendency to increase progressively with the expansion of wind power generation when the criteria are negatively correlated, as high costs for one criterion are likely connected to low costs for the other criterion. As an example, C^{nat} and C^{dis} are negatively correlated and result in the high PTI of 0.669. The correlation coefficient is negative for all paired comparison involving C^{nat}, which is an indication that on average, low values of C^{nat} for a potential wind turbine are connected to high values C^{gen}, C^{dis} and C^{land}, respectively. In contrast C^{land} and C^{gen} are positively correlated and result in a PTI of 0.148.

Whether a PTI is high or low thus depends on both the spatial correlation and the variability of the criteria. For example, the correlation coefficient does not have to be negative in order to allow for trade-offs and the PTI is dependent on both the variability and the correlation. In the comparison of C^{gen} and C^{land} with the lowest PTI, the correlation coefficient is positive (R=0.29) and the variability of both criteria is low, which in fact results in a low PTI of 0.148. Comparing C^{gen} and C^{dis} with a comparable correlation coefficient of 0.32 but a higher variability of C^{dis} consequentially results in a PTI of 0.492.

Overall, high potential trade-offs indicated by the PTI require the combination of high variability in at least one criterion and a negative correlation coefficient as contributing factors. A low variability in both criteria and a positive correlation coefficient in contrast prevent high potential trade-offs and PTIs.

3.2. Introducing an annual generation target of 200 TWh/a

Using the same Pareto frontier approach combined with an annual generation target of 200 TWh set as an additional constraint, the calculated feasible region yields a subset (green specific feasible region in Figure 4) of the overall feasible region which entails all solutions with an annual electricity generation of 200 TWh and allows for a direct comparison of costs and trade-offs for the given level of electricity generation. The specific form of the feasible region with its expansion on the x- and y-axis illustrates the trade-offs originating from the variability and spatial correlation of the two criteria. For example, in the paired comparison between C^{dis} and C^{nat}, the high variability in both criteria and a negative correlation leads to a large specific feasible region with high absolute differences with regard to the minimum cost (green dot) and maximum cost (red dot) for C^{dis} (ranging from 39 bn euros to 588 bn euros) and C^{nat} (ranging from the dimensionless value of 8,030 up to 65,664) in Figure 4. In contrast, the resulting specific feasible region for C^{gen} and C^{land} is far smaller and as the variability of C^{gen} is low, the feasible region is comparably thin on this axis compared to the axis for C^{land}.

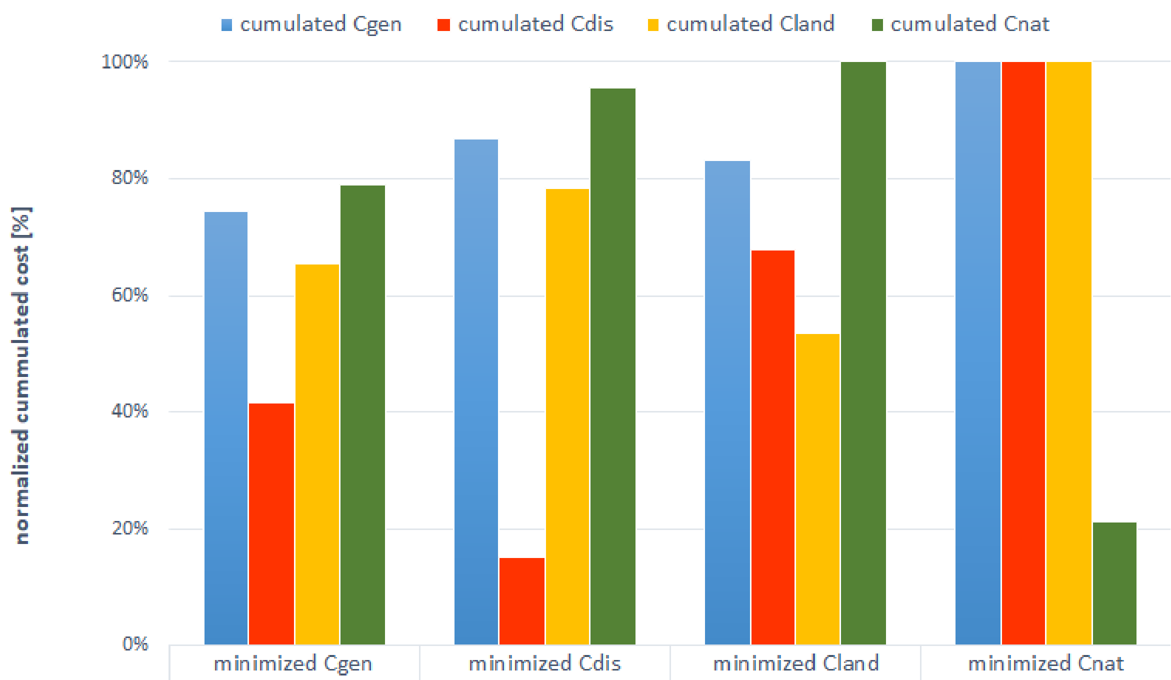
The trade-offs thus become apparent, as an identical generation target can be realized with significant cost differences for the connected costs for both criteria. And again, the specific feasible region, and thus the potential trade-off, is by far larger than the calculated trade-offs between the mono-criterial cost minima (indicated in Figure 4 by one green dot for each of the two criteria).

Further details on the trade-offs are provided in the table attached to Figure 6 below.

3.3. Comparison of the four mono-criterial cost minima for an annual generation target of 200 TWh/a

The comparison of mono-criterial optima for a generation target of 200 TWh/a contributes to the determination of trade-offs already presented in Figure 4, where the mono-criterial optima were marked as green dots in the graphs. This way, the trade-off is restricted to the single cost minima for each criteria and the comparison of mono-criterial optima for one criterion allows us to investigate the trade-offs with respect to the remaining three criteria.

The following graph provides an overview of the results for each of the four cost minima. While these minima are also part of the Pareto frontiers in the paired comparison for two selected criteria, Figure 6 also provides the connected costs for all other criteria, shown as percentages of the maximum cost in the respective criterion over all four minimizations. The number of required wind turbines to attain the generation target is also given in the table underneath the graph.



	minimized Cgen	minimized Cdis	minimized Cland	minimized Cnat
cumulated Cgen	74%	87%	83%	100%
cumulated Cdis	42%	15%	68%	100%
cumulated Cland	66%	78%	54%	100%
cumulated Cnat	79%	96%	100%	21%
No of WT	20898	24381	23407	28186

Figure 6: Resulting costs for the mono-criterial cost minimization of all four criteria for the 200 TWh/a generation target. Costs provided as percentages of the maximum result in the respective criterion over all four minimizations. The table underneath provides actual number of required wind turbines to achieve the generation target in the respective minimization.

The most significant trade-offs can be observed for the minimization of the criteria C^{nat}, as it leads to the highest cost for all remaining three criteria. The minimization of C^{nat} is thus responsible for the highest trade-offs in relation to all three remaining criteria. And when we minimize the costs for all other criteria, the costs for C^{nat} are significantly higher than when we minimize C^{nat}. This is consistent with the observation that C^{nat} is negatively correlated with all other criteria. The trade-offs are especially present in paired comparisons among criteria with a high variability, as is the case for C^{dis} and C^{nat}.

C^{gen} in contrast shows the least cost differences throughout all four mono-criterial solutions, in line with the already identified low variability of the criterion and the narrow form of the specific feasible region in the Pareto frontiers. With the set generation target of 200 TWh/a, the solution minimizing C^{gen} is likewise the one with the lowest number of required wind turbines. This is because C^{gen} itself is a function of the AEP of the wind turbine, so that the wind turbines with the highest AEP are the ones with the lowest generation costs and are therefore selected first. Accordingly, the number of required wind turbines increases from 20,898 (C^{gen}) to 23,407 (C^{land}) and 24,381 (C^{dis}) up to 28,196 (C^{nat}). The significantly higher overall number of required wind turbines compared to C^{gen} therefore also contributes to the trade-offs observed in the specific scenario with a set generation target.

The relevance of the different allocation criteria is likewise documented when comparing the resulting spatial allocation in the form of maps, as depicted in Figure 7. Regional differences in the allocation become apparent when comparing the four different mono-criterial solutions to the allocation problem.

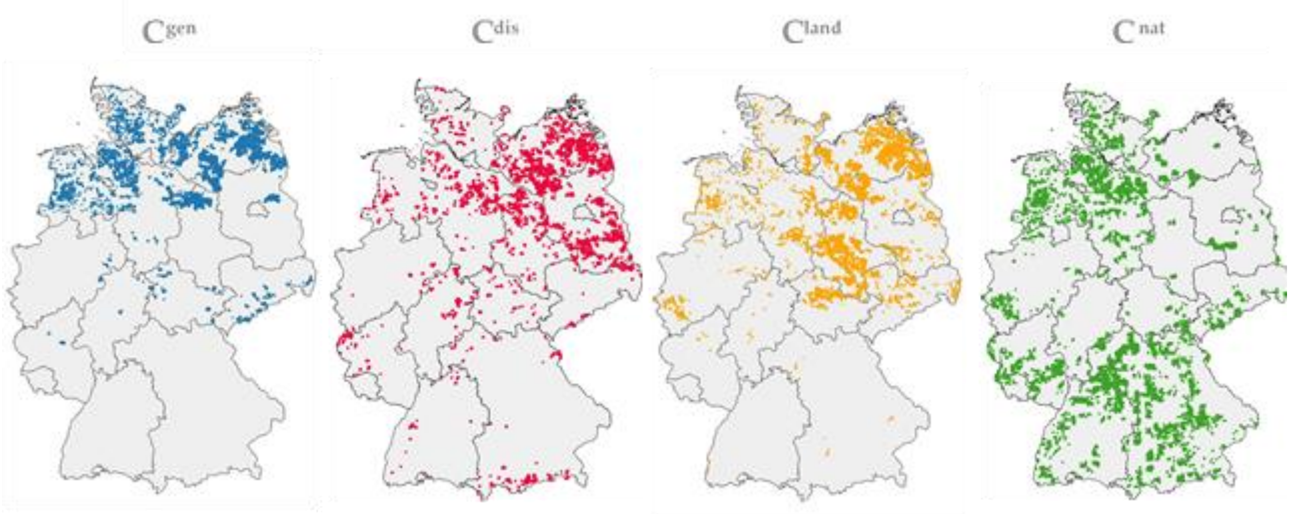


Figure 7: Resulting spatial allocation of wind turbines in the mono-criterial optimization of all four criteria for the 200 TWh/a generation target

The spatial patterns for the four presented mono-criterial optima clearly show how the different spatially heterogeneous criteria result in the distinctive spatial patterns on a national scale. As C^{gen} are dependent on wind resources, their minimization lead to an allocation of wind turbines in coastal regions in the north of Germany (blue markers); C^{dis} minimal allocation is affected by the settlement structure and the population density, so that the majority of wind turbines are allocated in the north-eastern part of Germany (red markers). A similar distribution can be observed for the allocation minimizing C^{land}, which also leads to a distinct concentration of wind turbines in the north-eastern part of Germany (yellow markers). In contrast, the allocation minimizing C^{nat} shows an almost inverted distribution, with wind turbines predominantly allocated outside the north-eastern parts of Germany (green markers). Here, the significant trade-offs already quantified by the PTI in the paired comparison of C^{dis} and C^{nat}, but also C^{land} and C^{nat}, directly materialize in the inter-regional spatial allocation patterns. This observation is likewise confirmed quantitatively by the fact that the correlation coefficient in all paired comparisons including C^{nat} is negative, while all other correlation coefficients are positive. The PTI, correlation coefficients and the spatial patterns of the mono-criterial allocation all complement the overall approach on determining the potential trade-offs among the criteria. These spatial patterns and trade-offs are also reflected when so called "no regret" potential sites that intersect when plotting the solutions for the different optimization (Figure 7) on top of each other are selected under different mono-criterial cost minimizations. The number of intersecting potential sites in the 11 possible paired combinations of the four criteria is provided in Table 1 below.

Table 1: Number of wind turbines (No of WT) and generated TWh/a in the intersection of all four mono-criterial cost minima for the 200 TWh/a generation target for all 11 possible combinations of criteria. Indices C^{gen}: generation cost, C^{dis}: disamenity cost, C^{land}: cost on the landscape quality, C^{nat}: cost on nature conservation

Combination of criteria	No of WT	TWh/a
Paired comparison		
$C^{gen} \wedge C^{land}$	9,490	90.2
$C^{gen} \wedge C^{dis}$	7,756	73.9
$C^{gen} \wedge C^{nat}$	7,260	72.1
$C^{dis} \wedge C^{land}$	5,817	53.0
$C^{dis} \wedge C^{nat}$	5,328	44.8
$C^{land} \wedge C^{nat}$	3,933	35.8
Paired comparison of three criteria		
$C^{gen} \wedge C^{dis} \wedge C^{land}$	3,932	37.3
$C^{gen} \wedge C^{land} \wedge C^{nat}$	2,166	21.6
$C^{gen} \wedge C^{dis} \wedge C^{nat}$	2,062	20.4
$C^{dis} \wedge C^{land} \wedge C^{nat}$	1,004	9.5
Paired comparison of four criteria		
$C^{gen} \wedge C^{dis} \wedge C^{land} \wedge C^{nat}$	731	7.3

The intersection of selected wind turbines in the mono-criterial solutions, which can be considered as a no-regret potential for a given generation target, leads to a significant reduction of both the remaining wind turbines and the energy generation from these wind turbines (see Table 1). When intersecting three or even all four mono-criterial solutions to identify no regret sites, the number of such intersecting sites further diminishes to 731 wind turbines with a mere 7.3 TWh/a from the original expansion target of 200 TWh/a in the single mono-criterial cost minima. This indicates that trade-offs among the established criteria are not only significant but inevitable in the further expansion of onshore wind power to achieve any expansion scenario in the transition towards renewables in Germany (Schlesinger, Hofer et al. 2010, Bundesregierung 2017, Agora 2018).

4. Discussion

4.1. Importance and drivers of spatial sustainability trade-offs

The results presented in the previous chapter will now be discussed to address the three initial research questions that this paper aims to answer. We were first of all interested in understanding whether trade-offs between the chosen criteria are significant for the allocation of onshore wind power. The results clearly showed that the feasible region formed by the Pareto frontiers may be substantial in size, meaning that trade-offs can be significant depending on the criteria selected in the paired comparison (Figure 4). By introducing the PTI for the overall and unrestricted feasible region, which is the main advancement of the presented approach, the potential trade-offs associated with the allocation of wind turbines have been visualized and quantified in six paired comparisons. Notably, the Pareto frontiers referred not only to the minimum cost solutions (lower frontier in the paired comparison graphs) but also to the maximum cost solutions. This approach helps to illustrate that the potential and the actual trade-offs can be far greater than those derived when comparing mono-criterial cost minima, as is commonly performed. This can be highly relevant as real world allocations are most probably not cost-minimal solutions for either of the criteria investigated. This is also underlined by the comparison of actual wind turbine allocations and different allocation optimizations performed by Eichhorn et al. (2019), where actual wind turbine allocations are estimated to cause much higher costs at an even lower energy generation (141 TWh/a) than the mono-criterial minima calculated by the authors.

How significant the trade-offs between different allocation criteria are is further documented by the spatial allocation patterns resulting from the mono-criterial optimizations. The allocation pattern for the 200 TWh/a generation target differs to a large extent up to the inter-regional scale, depending on the criteria selected. In this regard, the spatial allocation mapping for the 200 TWh/a expansion target spatially reflects the identified trade-offs among the four criteria. This stresses the inter-regional dimension of the allocation problem as the observed trade-offs originate from the spatial heterogeneity of the investigated criteria. A comparison of mono-criterial optima for different criteria by Eichhorn et al (2019) showed similar inter-regional allocation patterns with regard to the optimization of C^{gen} and C^{nat} as well as for C^{gen} and C^{dis} (Eichhorn, Tafarte et al. 2017, Tafarte and Lehmann 2019, Salomon, Drechsler et al. 2020). This was the case even though the criteria are modelled differently, using minimum distances from the individual wind turbine to the next nature conservation area as well as assuming a lower annual power generation target of 141 TWh/a instead of the 200 TWh/a in this case study. This likewise holds true for the general spatial patterns found by Gauglitz et al. (2019), although the modelling differs in detail. Consequently, the trade-offs also become apparent when the intersection of wind turbines which are selected in the four different mono-criterial optimizations, also regarded as "no regret" sites, are calculated. The intersection of all selected wind turbines in the four mono-criterial solutions reduces the number of wind turbines to 731, with a mere 7.3 TWh/a, compared to the original expansion target of 200 TWh/a for each of the single mono-criterial solutions which served as the input for the intersection. This indicates that the combined trade-offs among the established criteria are significant and that wind turbines with minor trade-offs between all four criteria are far too scarce to achieve future generation targets. This finding is also confirmed by Eichhorn et al. (Eichhorn, Tafarte et al. 2017)

Second, we also aimed to identify the criteria between which trade-offs matter most. Answers to this question can be derived from the differences in size and form of the overall feasible region and its quantification by the PTI. The PTI showed that the most significant potential trade-off is observed between C^{dis} and C^{nat} with a PTI of 0.669, so that lower C^{dis} can be traded to a larger extent for higher C^{nat} than for the other combinations of criteria. In contrast, this is the case to a much smaller extent between C^{gen} and C^{land}, with the smallest feasible region and a PTI of only 0.142. All PTI of the four remaining paired comparisons range in between, with values of 0.469 to 0.504. These insights align with the presented results for the specific generation target of 200 TWh/a, as most significant differences between the four mono-criterial solutions are observed for the combinations of criteria with the highest PTI. Most notably, the mono-criterial optimization for C^{nat} results in the highest trade-offs with regard to all other criteria. C^{nat} has likewise been identified as one of the criteria causing the highest trade-offs in previous studies on the optimal allocation of wind power in Germany (Eichhorn, Tafarte et al. 2017, Eichhorn, Masurowski et al. 2019, Gauglitz, Schicketanz et al. 2019). This similarity arises despite the fact that the criteria are modelled differently and the generation target varies (from 41 TWh/a (eastern Germany only (Eichhorn, Tafarte et al. 2017)) to 141 TWh/a (Eichhorn, Masurowski et al. 2019) and 269 TWh/a (Gauglitz, Schicketanz et al. 2019)) in all three studies.

The reason for the observed differences in spatial trade-offs can be traced back to two factors: the spatial heterogeneity of the criteria, as shown in the descriptive statistics, but also the spatial correlation between the compared criteria. For example, trade-offs are particularly pronounced between C^{nat} and other criteria because C^{nat} exhibits significant spatial heterogeneity and is the only criterion negatively correlated with all other criteria. The importance of such an underlying inter-regional correlation was also reported by other researchers in a case study for the allocation of wind turbines in Germany for the criteria C^{gen} and C^{nat} (Eichhorn and Drechsler 2010) or the distribution of wind power-sensitive birds (Busch, Trautmann et al. 2017). Another case study for Switzerland for the criteria generation cost and ecosystem services reported a similar inter-regional correlation (Egli, Bolliger et al. 2017).

Finally, we investigated how trade-offs evolve with increasing levels of wind power deployment. As we have shown in the six paired comparisons, all overall feasible regions have the characteristic that they first expand with higher generation targets and more wind turbines added. In parallel, the potential trade-offs expand. This is caused by the increasing degree of freedom for the allocation and the possibility to allocate cost-minimal or cost-maximal wind turbines. Beyond the point where potential trade-offs reach a maximum, the feasible region decreases again towards the full deployment of all wind turbines (778 TWh/a), where ultimately no degree of freedom remains. The specific form of the feasible region and the PTI provide information on the potential trade-offs to be encountered with in the course of the expansion of wind power. Given the 101 TWh/a of onshore wind generation in 2019 in Germany (BMWi 2020), which is only a fraction of the overall 778 TWh/a of the entire onshore wind power expansion potential assumed for Germany in this case study, potential trade-offs can therefore further increase in the coming years.

4.2. Limitations, methods and transferability

A critical review of the limitations and methods presented in this paper has to highlight the following issues. The applied set of 106,496 potential sites across Germany has been identified based on a GIS modelling which checks for technical and legal restrictions. However, these potential sites will realistically be further reduced as additional requirements are to be met during the permission process. Furthermore, the already mentioned regional concentration of selected wind turbines in the optimization will presumably face at least acceptance issues. Such a reduction of available wind turbines at preferable low cost sites could plausibly constrict the feasible region, lead to more dispersed allocation patterns and therefore affect sustainability trade-offs within the expansion of wind power. Depending on the generation target and thus the position of the specific feasible region within the overall feasible region, trade-offs may increase or decrease.

The modelling and calibration of the four criteria and the basis of the applied methods are all described in detail and are based on a solid literature review. Input data and applied methods are valid and reliable. However, the type of derived cost function and the parameterization of these functions that are applied on the input data are subject to uncertainty. Results are therefore potentially sensitive with regard to the modelling for the applied cost functions (Lehmann, Reutter et al. 2021). However, as the applied criteria have been investigated by other authors, the different modelling approaches on the cost functions reveal a conclusive picture with minor discrepancies on cost and trade-offs associated to onshore wind power. For example, the general costs and trade-offs identified between C^{gen} and C^{dis} (Eichhorn and Drechsler 2010, Eichhorn, Tafarte et al. 2017, Salomon, Drechsler et al. 2020, Lehmann, Reutter et al. 2021), C^{gen} and C^{land} (McKenna, Weinand et al. 2020) as well as C^{gen} and C^{nat} (Eichhorn, Masurowski et al. 2019, Gauglitz, Schicketanz et al. 2019) are consistent with the results obtained in this case study for Germany.

Another limitation to the applied optimization approach is the lacking coverage of potential cumulative effects associated with the allocation of wind turbines. Possible positive or negative cumulated effects may originate from the local and regional cumulation of wind turbines. They imply that the marginal cost of an additional wind turbine allocated locally or regionally increases (positive cumulative effect) or decreases (negative cumulated effect) as a function of the number of pre-existing wind turbines. The empirical evidence of cumulative effects is scarce and inconclusive (Ladenburg and Dahlgaard 2012, Schaub 2012, Ladenburg, Termansen et al. 2013, Miller, Brunsell et al. 2015, Dröes and Koster 2016, Lehmann, Reutter et al. 2021). Positive cumulative effects are documented for generation costs, as additional wind turbines create wake turbulences and reduce the AEP from other wind turbines in close proximity so that specific generation cost are increased. However, no clear indication for either overall positive or negative cumulative effects is documented in the literature for the remaining three criteria. With positive cumulative cost effects, the resulting allocation would shift towards a lower concentration of wind turbines in comparison to the calculated allocations presented in this paper as a more dispersed allocation avoids the added costs induced by positive cumulative effects. In turn, negative cumulative effects could be expected to further increase the concentration of allocated wind turbines at potential sites in proximity to each other. But as it is yet unclear to what extent cumulated effects, positive or negative, are relevant and how to appropriately operationalize the additional complexity and uncertainty in the modelling, we have excluded any cumulative effects in this paper.

With regard to the rapid technological developments in renewable technologies, one should also be aware that major technological developments in wind turbine technology will presumably have impacts on the associated criteria. State of the art wind turbines for example are more productive, so that the required number of wind turbines to achieve future generation targets can be reduced. Furthermore, system-friendly wind turbines can unlock sites with medium to low wind resources to become competitive against high wind speed sites and the trade-offs in relation to generation costs might be reduced as more potential sites offer comparable low generation costs (Tafarte, Das et al. 2014, Hirth and Müller 2016). As a consequence, the modelled wind turbine type in the 3 MW class should be updated with the latest type of wind turbines in order to better cover technological developments of onshore wind energy in coming years.

Adding further criteria for the allocation to internalize more aspects into the applied allocation logic of minimizing costs could contribute to improving the results. Such additional criteria could range from system integration costs, other renewable technologies as a substitute to the expansion of wind power, regional development goals and renewable targets, but also distributional justice for instance (Lehmann, Ammermann et al. 2021). However, integrating such complex criteria into an elaborated model would go beyond the GIS modelling approach in this paper and the goal of this study, which is to identify and quantify basic trade-offs for the allocation of wind turbines.

In general, it should be stressed that the provided approach and results do not aim of to identify the exact and overall optimal wind turbine sites across Germany, or to provide the cost-optimal allocation across Germany. Consequently, the results from the optimization should not be mistaken for a realistic expansion plan for wind power in Germany. Instead the intention is to improve the understanding of potential conflicts and trade-offs among the most relevant criteria for the expansion of wind power in a case study for Germany as well as the underlying drivers.

With regard to the transferability of the presented paper, the described approach of identifying and quantifying potential trade-offs and cost differences should be fully transferrable to other regions and also other technologies with a spatial impact on criteria. In contrast, the obtained results presented in this study are highly specific to the study area, as for example the variability and the correlation of the various relevant criteria differ from between regions. So results clearly cannot be transferred across study regions, as the spatial variability and correlation of criteria are specific to the investigated study region. For example, the analysis by McKenna et al. (McKenna, Weinand et al. 2020) revealed for Great Britain that there exists a strong positive spatial correlation between scenic landscape and wind resources, implying inevitable trade-offs between generation cost and the impact on the aesthetic landscape quality. For the case study on Germany, we identified this combination of criteria to be the least conflicting one in comparison to the other combinations of criteria.

5. Conclusion

Our empirical analysis and optimization determined and quantified the potential trade-offs between criteria selected for optimization for the allocation of wind turbines across Germany. These potential trade-offs vary significantly between the modelled criteria (generation costs, disamenity costs for residents, costs associated with the aesthetic landscape quality, costs for nature conservation). The provided trade-off analysis and comparison on mono-criterial optima for all four investigated criteria showed that trade-offs can be substantial and optimizing one criterion comes at the cost of trade-offs for another criterion. This is particularly the case for the criterion nature conservation, which consistently showed the highest specific trade-offs with regard to all other three criteria. High trade-offs are also identified for the criterion disamenity costs, whereas generation costs and landscape quality in contrast resulted in fewer trade-offs with regard to the other three criteria.

The decision on how to tackle trade-offs and opportunity cost for individual alternatives is therefore inevitable, as exemplified by the results of the 200 TWh/a allocation. Furthermore, these trade-offs are related to the variability as well as to the spatial heterogeneity of the criteria, so that depending on the criteria selected for an optimization, a regional reallocation is connected to these trade-offs.

As we have exemplified for a possible wind power generation target for the year 2030, there is no "optimal solution" or trade-off-free solution to the allocation problem, as the number of wind turbines that can be regarded as "no regret" solutions is insufficient to achieve any expansion scenario in the transition towards renewables in Germany. Therefore, the selection and weighting of relevant criteria is crucial as there may be no societal consensus and preferences for the optimal allocation of wind turbines can be rather heterogeneous in society and even among experts in the field (Lehmann, Ammermann et al. 2021). In this regard and from the point of view of the authors, a policy framework is needed that adequately considers all criteria identified as relevant by society. This is of high relevance as with the transition towards a sustainable energy transition, trade-offs and associated conflicts will almost certainly increase in parallel to the expansion of wind power and other renewable energy infrastructure. As trade-offs are inevitable and even the best policy response based on an idealized fully informed decision maker cannot avoid trade-offs, we conclude that a transparent public debate on which criteria should be relevant or most important and weighted accordingly would be the adequate proposal to this challenge.

Cost effectiveness in terms of generation costs has been crucial for a fast expansion of renewables and has commonly been set as the prime criterion to achieve cost competitiveness with non-renewable sources. However, as shown here, other criteria for the sustainable transition can be regarded as being of relevance, and an internalization of such criteria in the allocation process is therefore required. Support schemes should therefore either internalize these additional criteria or, if this is not possible, complementary instruments like regional planning, which is capable of integrating and coordinating diverse criteria in considerations, should be put in place to compensate for imperfect regulation of market-based instruments.

By introducing the concept of trade-off coefficients, we propose a novel perspective on the overall spatial allocation problem by estimating and quantifying the potential trade-offs between relevant criteria. Apart from the optimal (cost-minimal) allocation of wind turbines performed in this paper, a broader perspective on trade-offs is provided by the concept of the PTI. The identification and quantification of potential trade-offs beyond single cost-minimal solutions through the calculation of Pareto frontiers and the feasible region provides additional information on the characteristics of trade-offs between criteria. As shown, cost-minimal solutions make up only a minor fraction of the overall feasible region. Realising only these "optimally" allocated wind turbines might not be feasible with regard to its implementation, so that the knowledge of the overall feasible region and its potential for conflicts among criteria is of high practical and theoretical relevance. With regard to the question of how to manage the necessary expansion of onshore wind power in the future, the information on the potential conflicts and trade-offs described in this paper can provide useful information and an instrument for policy makers and researchers alike.

Based on the findings and on the current state of research on trade-offs in the spatial allocation of wind turbines, the addition of further relevant criteria to complement the existing set of criteria, like grid extension and integration costs, appears desirable. Adding further limitations and restrictions can likewise bring the results closer to politically feasible expansion scenarios, for example by limiting the number of wind turbines possibly allocated in each federal state region or minimal renewables shares targeted by the federal states or regions.

One important improvement to the established method can be expected from implementing cumulative effects on the criteria from the allocation of wind turbines, so that interdependencies from the allocation of individual wind turbines are covered by the optimization. And the perspective towards the power system integration can be improved by the introduction of other renewable energy sources into the presented spatially explicit trade-off analysis. Solar photovoltaics for example can substitute wind power generation to some extent but might be connected to additional trade-offs and criteria to be considered.

Finally, the mapping and assessment of the current wind turbine allocation in the feasible region can serve as an information base to assess the performance of the status quo with regard to the criteria (Latinopoulos and Kechagia 2015, Watson and Hudson 2015, Eichhorn, Masurowski et al. 2019).

6. Appendix

Table A1: List of wind power-sensitive bird species and input data for the operationalization of C^{nat} as a function of the recommended minimum distance for a wind turbine to the next bird nesting.

Species	scientific name	minimum distance [km]	circular area [km²]	normalized circular area [-]
Tree falcon	(Falco subbuteo)	0.5	0.79	0.007
Osprey	(Pandion haliaetus)	1	3.14	0.028
Great Bustard	(Otis tarda)	3	28.27	0.250
Hen harrier	(Circus cyaneus)	1	3.14	0.028
crane	(Grus grus)	0.5	0.79	0.007
Marsh harrier	(Circus aeruginosus)	1	3.14	0.028
Red kite	(Milvus milvus)	1.5	7.07	0.063
Lesser Spotted Eagle	(Aquila pomarina)	6	113.10	1.000
Black kite	(Milvus migrans)	1	3.14	0.028
Black stork	(Ciconia nigra)	3	28.27	0.250
White-tailed eagle	(Haliaeetus albicilla)	3	28.27	0.250
Golden eagle	(Aquila chrysaetos)	3	28.27	0.250
Short-eared Owl	(Asio flammeus)	1	3.14	0.028
Eagle owl	(Bubo bubo)	1	3.14	0.028
Peregrine falcon	(Falco peregrinus)	1	3.14	0.028
White stork	(Ciconia ciconia)	1	3.14	0.028
Honey buzzard	(Pernis apivorus)	1	3.14	0.028
Montagu's Harrier	(Circus pygargus)	1	3.14	0.028

7. Literature

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