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The future spatial distribution of onshore wind energy capacity based on a probabilistic investment calculus

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by

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Abstract

The spatial distribution of future renewable capacities is a key determinant for developing appropriate grid expansion plans. This is particularly relevant for onshore wind energy. Existing studies mostly extrapolate future installations based on existing capacities and available sites. As wind farm projects are developed mainly by private investors, the economic rationale of investing at specific sites deserves more attention. Therefore, the present contribution develops a model of economic choice for wind investments based on site-specific computations of the achievable net present value, taking into consideration the land availability at the regional level. Therefore, site-specific investment decisions are modeled as (partly aggregated) discrete choices. The net present value is computed from investment costs and expected yields, which can be estimated based on wind speed time series and power curves. Available land can be identified by excluding settlement, infrastructure, and nature conservation areas with appropriate buffers, as well as sites with topographically unsuitable profiles. The model is formulated as a nested logit model that captures the interdependencies between choices on two levels: the probability of investment in a particular region on the first level and the probability of installing a specific turbine type on the second level. In an application for Germany with the target capacities of the German Renewable Energy Act, the model delivers a spatial distribution of the capacities at the NUTS 3 level. The model also enables the derivation of the necessary compensation level and the most frequently installed turbine types.

Keywords: wind energy, regionalization models, renewable energy sources, nested logit model

JEL-Classification: Q42, Q48, C35, R58

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Content

Abbreviations and symbols

a_{n0}	Relative area per region which is not used for wind energy
α_{ni}	Estimation parameters for the benefit of a turbine i in region n
$a_{ni}^{used,DC}, a_{ni}$	Relative used wind energy area in the Discrete Choice Model
β	Estimation parameter – utility increase of an explanatory variable at lower level
B_k	Subset of all alternatives within nest k
γ	Estimation parameter – utility increase of an explanatory variable for nest at upper level
C_i^{inv}	Investment costs of turbine type
Cap^{base}	(total) installed capacity in the base year
Cap^{DC}	Capacity installed in the relevant Discrete Choice Model timespan
Cap^{sim}	Remaining capacity in simulation year of actual plants
Cap^{target}	Target capacity for the simulation year
$corr^{rem}$	Correction factor of remuneration
ε_{ni}	Unobservable utility of a group/region for alternative i
EEG	German Renewable Energy Act (Erneuerbare-Energien-Gesetz)
i	Specific alternative i
IC	(total) installed wind capacity (as model result)
I_{nk}	Inclusive Value for a group/region n for a nest k
j	General index for an alternative j (turbine type)
k	Index of a specific nest k
λ_k	Independence measure of unobservable utility
LCOE	Levelizd costs of electricity
LL	Log-likelihood function
LT	Turbine lifetime
n	Decision maker / region n
NPV	Net Present Value
NUTS 3	Nomenclature of territorial units for statistics, level 3
P_{ni}	Probability of choosing alternative i by user/region n; predicted market share
$P_{ni\|B_k}$	Probability of choosing specific alternative in the chosen nest (lower level)
P_{nk}	Probability of choosing a nest (upper level)
PP	Power potential: are consumption per capacity wind energy
π_{nj}	Probability of a group/region n deciding for alternative j
r	Interest rate
rem	Remuneration for a produced energy quantity
RES	Renewable Energy Sources
TP_i	Installed capacity/power of turbine type
U_{nj}	total utility of a group/region n for alternative j

V_{nj}	Total observable utility of a group/region n for an alternative j
W_{nk}	Observable utility of a group/region n for a nest k
WindBG	Wind Energy Area Requirement Act (Windenergieflächenbedarfsgesetz)
WP_{ni}	Wind energy production
x	General notation of an explanatory variable on the lower level
Y_{nj}	Observable utility of a group/region n for an alternative j
Z_{ni}	Infeed profit

1 Introduction

The ambitious goals of the European Union and its member states regarding climate neutrality in 2050 or even earlier require massive investments in renewable generation technologies. The power supply sector, where onshore wind energy plays a crucial role, is especially subject to a rapid and far-reaching transformation. To accelerate the renewable expansion, planning and approval processes have to be streamlined, and at the same time, sufficient areas have to be cleared for installation, cf. e.g. (Deutsche Bundesregierung, 2023).

The future regional distribution of renewable energy installations has, in turn, important implications, notably regarding the necessary expansion of the electricity grid to avoid bottlenecks. As such grid developments require long planning and construction times, an appropriate anticipation of the future renewable electricity infeed is required. Particularly relevant is the spatial distribution of onshore wind energy installations. The realization of capacity targets (e.g., in Germany defined by the Renewable Energy Act (EEG) (BMWK, 2023)) faces significant technical and socioeconomic obstacles, including land availability issues. Different decision-makers, such as private investors and grid operators under regulatory oversight, use various pragmatic methods to forecast renewable energy source (RES) investments. Yet, these often lack a robust economic foundation. We therefore propose a novel method that accounts for investors' choices mainly driven by expected profitability. Besides observable characteristics, unobservable factors such as credit restrictions or site-specific cost components influence profitability. Additionally, profitability is typically enhanced by selecting the turbine type best suited to the specific site.

In this paper, the spatial distribution of onshore wind energy investments is modeled as a set of site-specific discrete choices from which expansion probabilities are determined. Discrete choice models pioneered notably by (McFadden, 1974) have found widespread application in various fields since they provide a valuable and empirically testable framework for analyzing individual choices. E.g., in transportation demand analysis, individuals‘ travel behavior can be studied, including the selection of transport mode and route selection (Train, 2009) (Ben-Akiva & Lerman, 1985) (Vovsha & Bekhor, 1998) (Koppelman & Bhat, 2006). In the field of product marketing, nested logit models as an extension can help to understand consumer behavior and their choices among different brands or products. These are often organized in different nests based on their attributes (Ansari, et al., 1995). Also, energy-related choices have been addressed repeatedly, including electrical appliance holdings (Dublin & McFadden, 1984) (Weber, 1999) or heating system choice (Michelsen & Madlener, 2012) (Bauermann, 2016).

In the analysis at hand, the model approach is extended and adapted to investigate the probability of turbine installations on available sites. Therefore, a detailed data basis of wind turbine installations in Germany is used along with spatially disaggregated wind speed time series, and an engineering-economic cost model is applied to analyze investments and expected yields at each location. On the other hand, information on available areas for future investments is derived from a land use and spatial restriction analysis. This is combined with the obligations imposed by the federal government on the federal states regarding minimum wind investment areas to identify the expected future distribution of onshore wind investments.

Accordingly, this paper provides a novel approach (i) to analyze empirically the impact of economic profitability considerations and spatial restrictions on the allocation of wind power capacities, (ii) to investigate how regional and turbine characteristics are impacting jointly investment choices based on a nested logit model, and (iii) to assess the future deployment of wind turbines and how it is affected by regulatory settings both regarding land use and support mechanisms.

The remainder of this paper is structured as follows: Section 2 presents material and methods, contrasting conventional regionalization models on the one hand with discrete choice models on the other hand that form the basis of our investment modeling approach. It delves into the modeling steps of parameter estimation, wind yield modeling, profitability assessment, determination of suitable areas, and investment decision simulation. A case study is performed in Section 3, including the presentation of data sources, the parameter estimates, and the simulation outcomes. Section 4 provides a discussion, emphasizing key issues like land availability, profitability, and data quality. Finally, Section 5 concludes the paper.

2 Material and methods

In view of putting the newly developed method into context, Section 2.1 discusses the procedure used in typical "regionalization models", which are frequently applied for a spatial allocation of future wind energy capacities in the context of network development plans. The principles of discrete choice and nested logit models, which are at the heart of the novel methodology are reviewed in Section 2.2, and their application to an empirical analysis of wind energy investments is discussed in Section 2.3. Section 2.4 delves into the profitability of wind power plants, which is a key driver for investments, including the details of the underlying computation of wind yields. Section 2.5 describes the methodology used to identify suitable areas for wind energy installation, while Section 2.6 summarizes how these elements are brought together given the simulation of future wind energy investments.

2.1 Conventional and novel modeling for future wind capacity deployment

Most governmental capacity targets are initially established at higher planning levels, e.g., within national action plans (cf. (European Union, 2009)) or national renewable legislation (e.g. EEG 2023 (BMWK, 2023)). Regionalization models facilitate the breakdown of national or regional targets into smaller spatial areas, allowing for detailed planning and implementation. Such models are especially needed in the context of network expansion planning since required line capacities are strongly dependent on future grid usage – which in turn depends on the siting decisions for new plants broken down to the level of transmission grid nodes. Regionalization models, therefore, build on assessments of generation potentials such as (de Vries, et al., 2007), (Teske, et al., 2019), or (Miyake, et al., 2024). Yet beyond assessing regional potentials and constraints, regionalization models support the strategic development of energy infrastructure by estimating at a high spatial granularity which fraction of the identified potentials will be actually used.

As Germany is a frontrunner in the expansion of renewable energies and also pursues ambitious grid expansion plans (NEP 2023, (BNetzA & ÜNB, 2023a), (BNetzA & ÜNB, 2023b)), we subsequently take a closer look at existing studies on the regionalization of wind energy in Germany. These are typically divided into two main phases.

The first phase starts with an analysis of the existing power plants. This is followed by identifying suitable land areas, which involves assessing land areas using suitability indicators or more straightforward approaches dividing areas into suitable or non-suitable. The decision on which areas to consider or exclude is influenced to a certain extent by political considerations. Aspects like social acceptance may already be indirectly factored into the spatial analysis by incorporating buffers around exclusion areas – which may eventually be adjusted to state-specific legislation (Stede & May, 2019). The studies follow very similar approaches in this phase but differ in their level of detail. While (Matthes, et al., 2018) subtract identified exclusion areas on a more aggregated spatial level, (Bons, et al., 2023) combine designated areas from a regional planning level with a detailed white area analysis considering local specifications. A brief description of the methodology used in various studies is presented in Table 1.

In the second phase, the wind farm siting process determines the installed capacity and, depending on the spatial granularity level, even the precise geolocation of turbines. This is where the approaches of the various studies differ. (Schmid, et al., 2021) and (Pape & Geiger, 2023) follow a binary decision-making process where suitable land is converted into cells, and an algorithm decides whether a turbine can be built based on criteria such as collision with other turbines or minimizing the occupied area. Another approach is the proportional distribution of capacity based on the expected infeed, e.g., used by (Matthes, et al., 2018). (Moser, et al., 2020) utilizes a multi-criteria optimization approach to assign capacity and land targets to administrative regions without detailed turbine placement.

Table 1: Overview of relevant regionalization studies for Germany

Study	Identification of suitable areas	Windfarm siting
(Bons, et al., 2023)	Use of a comprehensive database of area designations at the level of regional planning considering uncertain factors such as minimum distance regulations. Establishment of a binary coding on an area grid indicating the suitability of each grid element.	Based on (Thiele, et al., 2021): Computation of the maximum number of turbines while adhering to elliptical minimum distances (5 rotor diameters in the main and 3 in the secondary wind direction) and considering existing installations.
(Pape & Geiger, 2023)	Identification of areas in principle suitable for expansion and evaluation based on the probability of expansion derived from prevailing wind conditions. Geodata-based modeling considering restriction criteria and corresponding distance requirements.	Site-specific placement considering elliptical minimum distances. Method to calculate the maximum number of WEA per available area.
(Schmid, et al., 2021)	Analysis of currently designated areas for wind farms, including already installed turbines. Determination of available area using typical distance ellipses and derivation of corresponding electrical expansion potential. Evaluation of restriction classes to determine the rated potential.	Placement follows typical distance ellipses to determine available areas for new installations. The order of development follows site classes and develops areas according to their ranking based on potential wind energy yield.
(Matthes, et al., 2018)	Analysis of area availabilities and restrictions to determine utilization potential. Identification of exclusion areas on a more aggregated spatial level.	Placement of installations considering both technological and spatial differentiation of areas and optimizing land-use w.r.t. area restrictions and conservation interests.
(Moser, et al., 2020)	Identification of land suitability of grid cells. Consideration of a range of exclusion criteria.	Use multi-criteria optimization with various drivers, including economic viability, land suitability, societal factors, and regulatory instruments.

These regionalization studies include detailed analyses of area potentials and employ methods to place turbines according to expected yields and compliance with regulations. However, for reliable and realistic future scenarios in onshore wind expansion, it is crucial also to conduct consistent economic analyses. Only (Moser, et al., 2020) consider economic criteria explicitly, including the Levelized Costs of Electricity (LCOE) as one of the criteria in the developed multi-criteria optimization approach. LCOE provides an estimate of the costs of electricity generation per unit but does not consider the revenue side nor take into account potential unobserved heterogeneity of both investment opportunities and investors. As described in detail below, our approach addresses the first point by utilizing the Net Present Value (NPV), offering a financial picture that includes all cash flows over a turbine's lifetime. Additionally, our model incorporates potential unobserved heterogeneity in a consistent way through discrete choice models and a hierarchical decision-making process. By considering both observable and unobservable utility components, the novel approach enables economically more consistent and realistic modeling of investment decisions, accounting for regional economic viability more effectively.

The novel approach is summarized in Figure 1, and the description of the different parts of the methodology is given in the next sections following the sequence indicated in the figure.

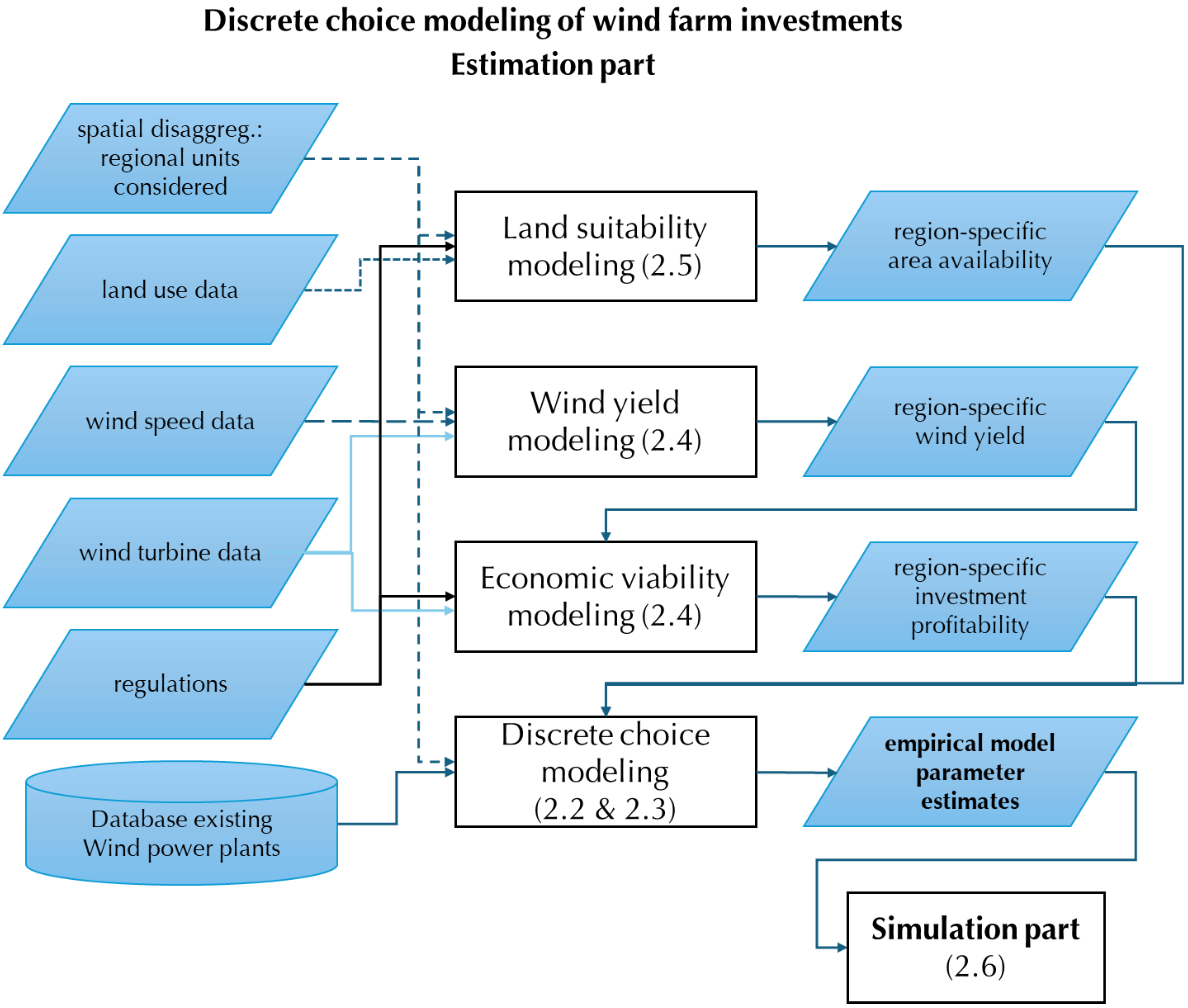

Figure 1: Novel modeling approach for wind energy investments

2.2 Modeling wind energy investments using discrete choice models

Discrete choice models have been developed by Daniel McFadden and others (e.g. (McFadden, 1974)) to empirically investigate cases where decision-makers choose a particular alternative out of a limited number of alternatives. Discrete choice models examine the relationship between a discrete or categorical dependent variable and explanatory variables, which may be scaled metrically or categorically. (Train, 2009)

The decision regarding an investment in wind power plants at a potential location corresponds basically to the binary choice between "invest" and "not invest" and may, hence, be modeled using a standard binary logit model. This model allows assessing the probability of each alternative based on key explanatory variables. The logit specification has the advantage that explicit formulas for the choice probabilities may be given.

At a more detailed level, investing in wind farms requires the choice of an appropriate turbine type, and this may be considered in a discrete choice model through a second decision stage – as included notably in the so-called nested logit models (Train, 2009). This model class may account for the dependency of the turbine choice on the prior investment decision – and vice versa, as well as the dependency of the investment decision on the availability of an appropriate turbine type. This follows from the principles of rational choice underlying discrete choice models – a rational decision-maker will take into account the consequences of her choice - including the implications of subsequent choices. Accordingly, various studies, including those by (Daly & Zachary, 1987), (McFadden, 1978) and (Williams, 1977), have demonstrated that the nested logit model aligns with the principles of utility maximization.

The nested logit model can be structured with the upper level representing the decision to invest or not and the lower level representing the choice of turbine type if the investment is made (cf. Figure 2). The decision structure is divided into nests, with one nest corresponding to the choice not to invest and the other nest representing the choice to invest, which includes sub-alternatives of different turbine types. The probability of choosing a specific alternative within this nest depends on both the attributes of the alternatives and the attributes of the nest. For any (two) alternatives in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives. This property of "independence of irrelevant alternatives" or in short IIA holds within each nest. For any (two) alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the nests. IIA does not hold in general for alternatives in different nests (Train, 2009).

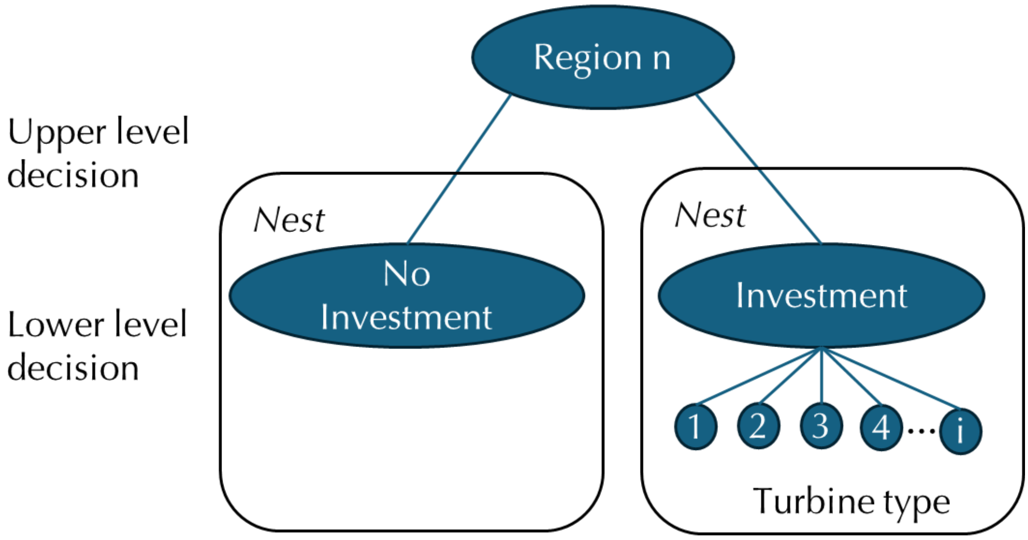

Figure 2: Nested structure of an investment decision in wind energy

In the vein of discrete choice models, the selection of an alternative primarily depends on the decision maker's utility, which is not directly observable and comprises both observable and unobservable components (cf. Section 2.3). In the case of wind energy investments, the utility for the investor basically corresponds to the economic profits obtained. According to standard finance theory, the net present value (NPV) is an adequate measure of profitability, with initial investment costs being subtracted from discounted future cash flows (cf. Section 2.4).

In the general case, the probability of decision maker n selecting one discrete alternative j over another is determined by comparing their utilities $U_{nj} = V_{nj} + \varepsilon_{nj}$. This utility is additively composed of an observable part V_{nj} and an unobservable part ε_{nj} for which an extreme value distribution is assumed in the case of the logit model. The choice probability is then derived based on the cumulative distribution function of the error terms. For the logit model, a closed-form expression for the choice probability may be derived, cf. (Train, 2009) and (Ben-Akiva & Lerman, 1985). Writing the observable utility $V_{nj} = \beta' x_{nj}$ as a linear function of the vector x_{nj} of observable variables, we obtain:

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{1}$$

For the nested logit model, the probability P_{ni} (cf. Eq. (*2*)) of choosing alternative $i \in B_k$ in region n is the product of the probability P_{nB_k} (cf. Eq. (*3*)) that an alternative within nest B_k is chosen (upper level) and the probability $P_{ni|B_k}$ (cf. Eq. (*4*)) that the alternative i is chosen on the lower level, given that the alternative B_k has been chosen.

$$P_{ni} = P_{ni|B_k} P_{nB_k} \tag{2}$$

$$P_{nB_k} = \pi_{nk} = \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{W_{nl}+\lambda_l I_{nl}}} \tag{3}$$

$$P_{ni|B_k} = \pi_{ni} = \frac{e^{\frac{Y_{ni}}{\lambda_k}}}{\sum_{j\in B_k} e^{\frac{Y_{nj}}{\lambda_k}}} \tag{4}$$

The total utility U_{nj} is thereby divided into two observable parts W_{nk} and Y_{ni} plus the unobservable part, where W_{nk} is the nest specific utility that depends only on variables that describe nest k. These differ between nests but not across alternatives within each nest. The other component Y_{nj}, the utility of alternative j in nest k, depends on variables that describe alternative j and vary across the alternatives within nest k. The parameter λ_k ($\lambda_k \in [0, 1]$) thereby serves as a measure of the degree of independence in unobserved utility among the alternatives within a nest B_k. A value of one indicates complete independence, and the nested logit model reduces, in this case, to a standard multinomial logit model. The nested logit model is thus a generalization of the logit model that allows for specific patterns of correlation in the unobserved utility. The inclusive value I_{nk} (cf. Eq. (5)) links the levels by transferring information from the lower to the upper model. It corresponds to the logarithm of the denominator in the lower model and $\lambda_k I_{nk}$ is the expected utility that the decision maker obtains when choosing among the alternatives in nest B_k.

$$I_{nk} = \ln\left(\sum_{j\in B_k} e^{\frac{Y_{nj}}{\lambda_k}}\right) \tag{5}$$

2.3 Choice model specification and parameter estimation

Based on the previous considerations, a nested logit model is set up to explain the observed investments in wind turbines of types i in locations n based on the net present value NPV of the different investment alternatives (cf. Section 2.4) . Thereby the logarithm of the NPV is used as the explanatory variable, both to prevent numerical issues related to large exponents and to reflect that the marginal NPV impact may be decreasing. The impact strength is given by the parameter β. Additionally, some idiosyncratic utility α_i associated with the different turbine types is included in the specification of equation (6) – this may, e.g., reflect limitations in allowable hub heights in some locations. The observable utility Y_{ni} associated with alternative i in location n is thus written:

$$Y_{ni} = \alpha_i + \beta \cdot \ln(NPV_{ni}) \tag{6}$$

For investment decisions, often detailed data is available on the invested wind turbines. However, information is scarce on those areas that are, in principle, suitable for investment yet have not been retained. Therefore, estimation is only feasible based on semi-aggregated data, i.e. using observations at the regional scale regarding the share of suitable area that has been actually used for investment. a_{ni} is the area share used in region n for investments in turbine type i. Correspondingly, we define $a_{n0} = 1 - \sum_i a_{ni}$ as the share of suitable areas in region n which is not used for wind energy investment.

Applying a nested logit model with the binary choice between the alternatives of investing or not investing at the upper level, we obtain the following log-likelihood function:

$$LL(\beta, \gamma, \lambda) = \sum_n \sum_i \left(a_{ni} \cdot \left(\ln\left(P_{ni|B_1}\right) + \ln(P_{n1}) \right) \right) + a_{n0} \cdot \ln\left(P_{n0}\right) \quad . \tag{7}$$

Inserting the choice probabilities from Eq. (3) and Eq. (4) as well as the expression for the observable utility from Eq. (6), leads to :

$$\begin{aligned} LL(\beta, \gamma, \lambda) = \sum_n \Bigg(& \sum_i a_{ni} \cdot \left(\ln\left(\frac{e^{\frac{\alpha_i + \beta \cdot \ln(NPV_{ni})}{\lambda}}}{\sum_{j \in B_k} e^{\frac{\alpha_j + \beta \cdot \ln(NPV_{nj})}{\lambda}}} \right) + \ln\left(\frac{e^{\gamma + \lambda I_n}}{1 + e^{\gamma + \lambda I_n}} \right) \right) \\ & + a_{n0} \ln\left(\frac{1}{1 + e^{\gamma + \lambda I_n}} \right) \Bigg) \end{aligned} \tag{8}$$

The parameter values can be estimated by minimizing the negative log-likelihood function from an arbitrary starting point. α_i then represents the idiosyncratic utility of turbine i – which describes a natural preference for that turbine type. This idiosyncratic utility is not driven by economic viability but can be inferred from past installation practice. β indicates the utility increase related to an increase in profitability on the lower level, and γ is the idiosyncratic utility of investment at the upper level. λ is a measure of independence for the unobservable utility of the different turbine types.

2.4 Investment profitability assessment and wind yield modeling

Given that we expect wind energy investments to be driven by their expected profitability, we must calculate the net present value (NPV) per turbine type i for each region n. Therefore, we compute the wind yield based on wind speed data from weather databases for representative locations within each region. The wind speed data must be adjusted to depict the wind speed at the hub height of turbine type i, which in turn drives the wind energy yield.

For the extrapolation to the hub height, the so-called Power Law (Brower, 2012) is implemented. Based on the wind speed at hub height, the corresponding wind production WP_{ni} can be derived from the specific power curve of turbine type i. The modeling must additionally consider losses caused by both wake effects (shading) as well as technical and regulatory unavailability. The availability of the turbines is set to a blanket value of 0.97 (Conroy, et al., 2011) (Pfaffel, et al., 2017). Wake effects are approximated based on (Knorr, 2016), who determines an average wind efficiency characteristic curve for wind turbines in Germany, which can be used to estimate the wind speed reductions due to shading. The wake effect depends on the wind speed; losses are typically in the range between 4 and 15 ms^{-1}.

For an appropriate assessment of the economic profitability, the link between wind energy yield and revenues has also to be considered. In Germany, wind energy investors receive a guaranteed feed-in remuneration rem, which is under the current legislation determined via auctions, cf. § 28 EEG (BMWK, 2023). Yet the German Renewable Energy Law (EEG) also includes some provisions to make the installation and operation of wind turbines economically viable at locations with weaker winds. The intention is to avoid overinvestment in regions with good wind conditions, which would exacerbate further the need for grid expansion. The law, therefore, foresees a compensation correction factor $corr_{ni}^{rem}$ derived from a so-called reference yield model. It is determined based on the simulated energy output for the turbine type at the envisaged location in relation to the reference yield for the turbine type at a reference location. Plant operators in less windy locations receive a higher payment per kilowatt hour of electricity generated, while those in windy locations receive a lower payment. (cf. § 36 et seq. EEG 2023 (BMWK, 2023))

Correspondingly, the infeed revenue Z_{ni} may be calculated for each region and turbine type according to:

$$Z_{ni} = rem \cdot corr_{ni}^{rem} \cdot WP_{ni} \quad \forall\, n, i \tag{9}$$

Finally, the NPV_{ni} per region and turbine type is obtained under consideration of the investment cost C_i^{inv}, interest rate r and lifetime LT as:

$$NPV_{ni} = -C_i^{inv} + Z_{ni} \cdot \frac{(1+r)^{LT} - 1}{(1+r)^{LT} \cdot r} \quad \forall\, n, i \tag{10}$$

Given that wind energy investments are analyzed in the context of limited land resources, it is essential to account for land use efficiencies. To achieve this, we adjust the explanatory variable NPV by dividing it by the used area, which is determined as the installed capacity of the respective turbine type (cf. Table 3) divided by the power potential (cf. Section 3.2).

2.5 Determination of suitable and used wind areas

A GIS-based area restriction analysis is implemented to identify the maximum possible installed capacity for each region. Starting from the total regional surface area, areas unsuitable for installing wind energy plants are subtracted, like forest, traffic, and water areas, as well as areas with strong slopes. State-level legislation in Germany imposes minimum distances of wind turbines from settlement areas which leads to an exclusion of these areas from the suitable area. Furthermore, nature conservation areas and airport grounds, including the corresponding landing paths, are excluded. Figure 3 shows the identification of possible areas for wind energy for two exemplary NUTS 3 regions, DEA33 (Münster) and DEA38 (Warendorf).

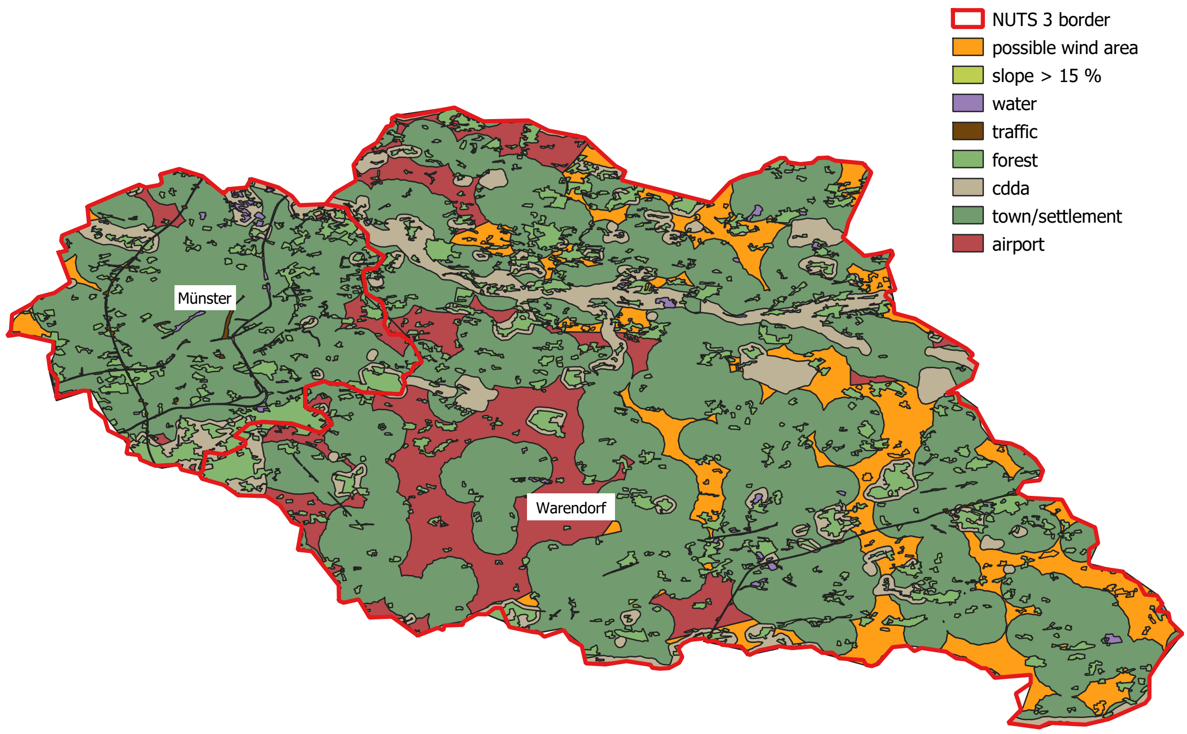

Figure 3: Identification of exclusion and wind areas

This analysis provides an upper limit for the areas suitable for wind energy investments. In fact, not all suitable areas have been declared by the regional authorities as designated areas or suitable areas for wind energy (cf. (Bons, et al., 2023) and Table 2). Therefore, some adjustments concerning the suitable areas must be implemented for the parameter estimation to consider the actual circumstances for past investments as realistically as possible. The suitable areas identified through the GIS analysis have hence to be calibrated to match the area target at the federal-state level for 2021, as indicated by (Bons, et al., 2023).

For future investments, different rules may be applicable. Notably, the German government decided to set aside 2 % of the total land area for wind energy by 2032 (Deutsche Bundesregierung, 2023) to reach its climate targets. To achieve a fair burden sharing among federal states while taking into account the specificities of the states (notably little suitable areas in urban regions), binding area targets (area contribution values) for every federal state until 2032 have been defined by law (cf. WindBG §3 Abs. 1). In Table 2, the corresponding shares of the total areas of the federal states and the whole country are shown along with those determined from the own GIS analysis and the designated areas in 2021. At the NUTS 3 level, the WindBG is interpreted as a lower bound for land allocation. In cases where a region has already developed a larger area share for wind energy installations in the base year than the area determined through scaling with the state-specific contribution targets, the existing share is retained, along with an additional buffer. This ensures that the model maintains flexibility and enables advantageous regions to invest in additional capacities for economic reasons.

Table 2: Area for wind energy by federal state

NUTS Code	Federal State	Total area [km²]	Percentage suitable areas for wind energy according to GIS-analysis	Percentage of designated areas in 2021 (Bons, et al., 2023)	Percentage of designated areas for wind energy according to (WindBG §3 Abs. 1)
DE1	Baden-Württemberg	35 747.82	16.08 %	0.5 %	1.8 %
DE2	Bavaria	70 541.57	2.43 %	0.7 %	1.8 %
DE3	Berlin	891,12	0.11 %	0.0 %	0.5 %
DE4	Brandenburg	29 654.35	14.62 %	0.8 %[1]	2.2 %
DE5	Bremen	419.62	1.08 %	0.8 %	0.5 %
DE6	Hamburg	755.09	3.37 %	0.2 %	0.5 %
DE7	Hesse	21 115.64	6.99 %	1.8 %	2.2 %
DE8	Mecklenburg-Western Pomerania	23 295.45	20.01 %	0.2 %	2.1 %
DE9	Lower Saxony	47 709.82	34.21 %	1.0 %	2.2 %
DEA	North Rhine-Westphalia	34 112.44	3.91 %	1.0 %	1.8 %
DEB	Rhineland-Palatinate	19 858.00	8.06 %	1.5 %	2.2 %
DEC	Saarland	2 571.11	4.17 %	1.8 %	1.8 %
DED	Saxony	18 449.93	6.90 %	0.2 %	2.0 %
DEE	Saxony-Anhalt	20 459.12	16.60 %	0.8 %	2.2 %
DEF	Schleswig-Holstein	15 804.30	25.96 %	2.0 %	2.0 %
DEG	Thuringia	16 202.39	14.70 %	0.3 %	2.2 %

[1] Assumed value for Brandenburg, as all plans here have been declared invalid by the courts and therefore there are currently no legally designated areas.

DE	Germany	357 587.77	13.56 %	0.79 %	2.0 %

To link the investment decisions to land use, the average power potential PP expressed in MW/km^2 is used. For parameter estimation and investment simulation (cf. Section 2.6), the suitable area from the GIS-analysis must be corrected for the area already occupied by existing wind turbines in the corresponding time period. For a realistic parameter estimation, the suitable area is scaled with the historical designated areas from (Bons, et al., 2023), resulting in $A^{designated}$. The area $A_{ni}^{DC} = \frac{Cap_{ni}^{DC}}{PP}$ used for wind turbines of type i in region n in the period relevant for the discrete choice model is then put in relation to the designated area $A_n^{designated}$ to derive the (historical) area investment probability $a_{ni} = \frac{A_{ni}^{DC}}{A_n^{designated}}$, which is the explained variable in the discrete choice model.

2.6 Simulation of future investment decisions

Making use of the estimated parameters from the empirical analysis, future investment decisions on a regional level may be determined if remuneration rules are fixed or capacity targets are preset. Based on a predetermined compensation, the NPV for each turbine type and region may be calculated according to equation (*10*). In a next step, the predicted investment probability P_{ni} is determined as a product of the probability of choosing a nest P_{nk} and the probability of choosing the specific alternative given the choice of the nest $P_{ni|B_k}$ (cf. Section 2.3):

$$P_{ni} = \frac{e^{\frac{\alpha_i + \beta \cdot \ln(NPV_{ni})}{\lambda}}}{\sum_{j \in B_k} e^{\frac{\alpha_j + \beta \cdot \ln(NPV_{nj})}{\lambda}}} \cdot \frac{e^{\gamma + \lambda \cdot I_{nk}}}{1 + e^{\gamma + \lambda \cdot I_{nk}}} \tag{11}$$

The total installed capacity IC may then be computed based on the designated area for wind energy in the simulation year $A_n^{designated,sim}$, the power potential PP and the choice probabilities P_{ni}:

$$IC = \sum_i \sum_n A_n^{designated,sim} \cdot PP \cdot P_{ni} + Cap_{ni}^{sim} \tag{12}$$

The total capacity is thereby adjusted by Cap_{ni}^{sim}, the capacities of the current fleet that are still active in the simulation year. To determine the designated area in the simulation year, the identified suitable area is scaled based on the federal states' contribution targets (BMWK, 2022).

In case a target capacity is given for the simulation year, an iterative approach may be used (cf. Figure 4). If the installed capacity is lower than the target capacity, the remuneration (initial price) is increased and vice versa until the target is fulfilled.

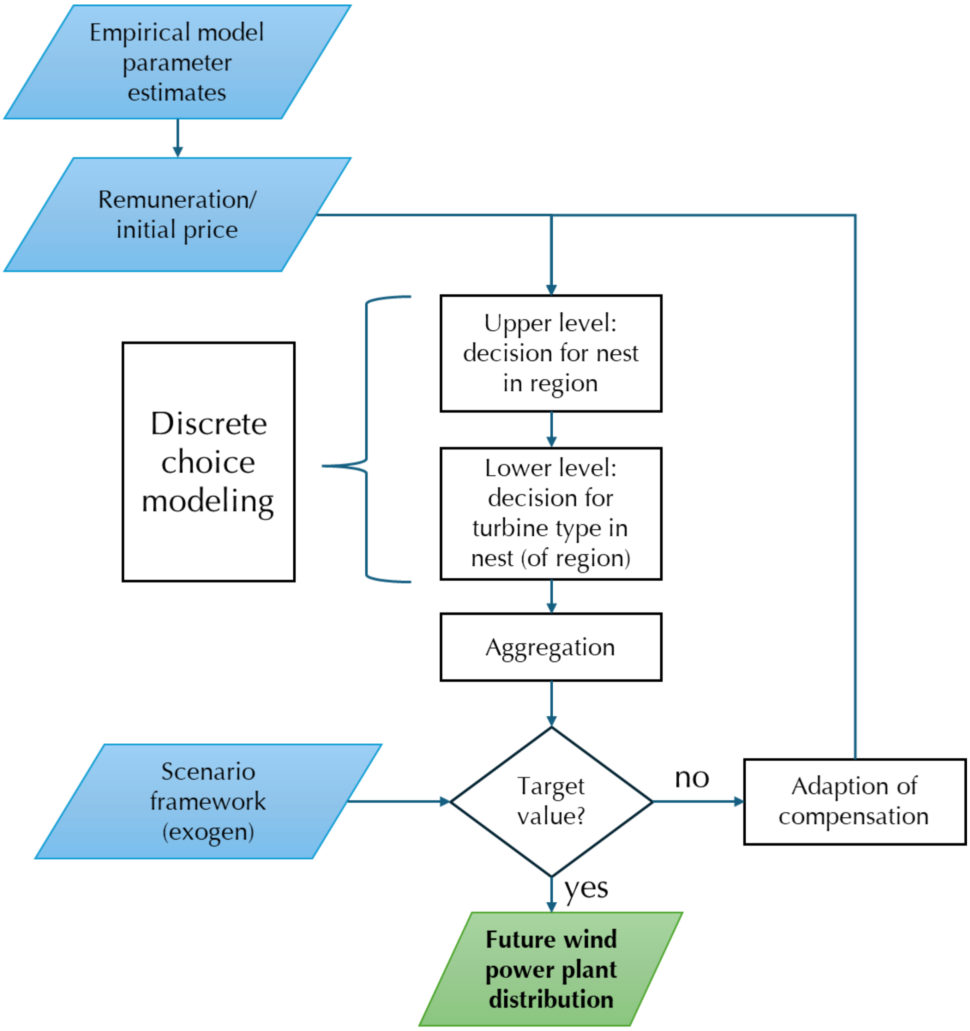

Figure 4: Flowchart of the iterative approach for matching a capacity target in the simulation year

3 Application and results

In this section, an exemplary application of the novel methodology to wind energy investments in Germany is presented. The used data are discussed in Section 3.1. Section 3.2 outlines several general settings that are crucial for further calculations in the nested logit framework. The results of the model application are presented in two parts. Section 3.3 focuses on the estimation of the parameters, including a discussion of the key parameters in terms of their interpretation and significance in decision-making. Section 3.4 delves into investment decisions based on the calculated parameters. Results for various simulation years are presented, accompanied by visualizations illustrating trends over time.

3.1 Data

The dataset on the current German onshore wind power fleet originates from the *Marktstammdatenregister*, the official register published by the German Federal Network Agency (BNetzA, 2022). Data from *Thewindpower.net* are used for power curves and turbine data (thewindpower, 2022). The turbines are aggregated to 8 turbine types based on (Pöstges & Weber, 2023). For each type, hub height, rotor diameter, net power, and CAPEX are given in Table 3. For future years, we follow (IRENA, 2024) and (Kost, et al., 2024) and assume an annual cost reduction by approximately 2.4 %, resulting in cost reductions of 17.5 % b 2030, 26.9 % in 2035 and 35.2 % in 2040. Regarding, the targets for areas and future capacities of installed onshore wind energy, the official targets set by the German federal government (BMWK, 2022).

Table 3: Technology data of representative onshore wind turbines (Pöstges & Weber, 2023)

Turbine Type	Hub height [m]	Rotor diameter [m]	Net power [kW]	CAPEX [EUR/kW]
1	72	53	800	1,047
2	139	121	2530	1,571
3	109	92	2350	1,155
4	142	114	3170	1,290
5	110	109	3000	1,169
6	150	140	4000	1,573
7	120	124	4500	1,363
8	120	140	6000	1,483

For weather information, we use ERA5 reanalysis data from the ECMWF Copernicus Store (Hersbach, et al., 2023), where wind speed data are given for 10 and 100 meters above the ground.

Data on exclusion areas due to settlement, forestation, traffic, water, airports, and slope gradient are provided by the *Copernicus Land Monitoring Service* (European Union, 2018) and the *WMS Digitales Geländemodell* (BKG, 2023). The EU has databases of nature conservation areas – in particular, *Nationally designated areas* (European Union, 2022). As regions, NUTS 3-regions are considered, defined after the European classification of territorial units for statistics (EU, 2015). In Germany, they correspond to the districts and district-free cities.

3.2 General settings

To apply the discrete choice framework to wind power plant investment decisions in Germany, certain parameters and assumptions must be established initially.

For the empirical application, the base year 2022 is chosen and the considered simulation years are 2030, 2035, and 2040 – years with legally fixed capacity targets Cap^{target} (cf. § 4 EEG 2023 (BMWK, 2023)). For the parameter estimation of the discrete choice model, investments from the ten preceding years are considered, i.e. from 2013 to 2022, to cover a sufficient number of installations. Over these years, there has been some variation in the remuneration levels, yet to assess the site-specific economic viability, a fixed remuneration level rem of 0.08 EUR/kWh is used, along with a constant interest rate r of 3.5 %. The turbine lifetime LT is set to 22 years (Pape & Geiger, 2023) (Schmid, et al., 2021) and for the power potential PP, the capacity that can be installed in a certain area, a value of 22.5 MW/km^2 is assumed based on (Matthes, et al., 2018) (discussed in Section 4). In the calculations for future investment decisions, we assume technological progress, which leads to an increase in power potential to 25 MW/km^2.

The weather year 2021 is used to simulate wind speed time series for further modeling. Results for a collection of several weather years yield similar outcomes, and corresponding parameters and target remuneration levels are provided in Appendix A. For the base year, the input dataset of turbines is initiated, with the capacities Cap^{base} containing all turbines installed in the preceding LT years. The capacities of the current fleet that are still active in the simulation year Cap^{sim} are the capacities installed in the LT years preceding the simulation year.

3.3 Parameter estimates

We implemented the introduced model with the corresponding data and parameters in MATLAB. The log-likelihood function is maximized using the quasi-Newton algorithm. The results of the parameter estimation regarding existing wind turbines are presented in Table 4. Since turbine type 4 is the most common turbine, it is designated as the reference type. For the other seven turbine types, the idiosyncratic preferences compared to the reference type are indicated by the parameters α_i given in the table.

Table 4: Parameter estimation results

Parameter	Estimate	Standard Error	t Statistic	
$\boldsymbol{\beta}$	4.4392	1.1950	3.7149	***
$\boldsymbol{\gamma}$	-79.0614	21.287	-3.7141	***
$\boldsymbol{\lambda}$	0.9521	0.2534	3.7567	***
$\boldsymbol{\alpha_1}$	1.1350	0.4670	2.4304	*
$\boldsymbol{\alpha_2}$	-0.5687	0.2395	-2.3744	*
$\boldsymbol{\alpha_3}$	0.6747	0.2558	2.6380	**
$\boldsymbol{\alpha_5}$	-0.5082	0.2812	-1.8076	
$\boldsymbol{\alpha_6}$	-0.7927	0.3122	-2.5394	**
$\boldsymbol{\alpha_7}$	-0.3829	0.4290	-0.8925	
$\boldsymbol{\alpha_8}$	-0.4597	0.6425	-0.7155	
R^2		0.1896		

*** p<0.05, ** p<0.01, *** p<0.001**

It should be noted that, e.g., a negative α_8 indicates that the large, high-capacity type 8 was often not chosen despite a high NPV, which may attributed to height restrictions in land use regulations or expected disamenity costs (Ruhnau, et al., 2022). β describes the utility increase per unit increase in the explanatory variable ln(NPV) at the lower level. The parameter γ describes a correction term for the inclusive value I_{nk} in the upper nest. A strongly negative value indicates that the aggregated utility I_{nk} (cf. Eq. (*5*)) derived for the investment alternatives in the lower nest has to be adjusted downwards when comparing it with the (zero) utility of the non-investment alternative (cf. Eq. (*11*)). All parameters, apart from three α_i, are significantly different from zero at least at the 5 % level. Yet the independence measure λ_k of the unobservable utility is not significantly different from 1, indicating that the error terms in the lower nest are also independent of those of the zero-investment alternative.

Following (Train, 2009), we report as a measure of determination R^2 a log-likelihood ratio, defined as one minus the log-likelihood value at the estimated parameters divided by the log-likelihood value at zero parameters. Unlike the conventional R^2 used in linear models, it has no intuitive interpretation for values between the extremes of zero and one. The value of 0.1896 indicates clearly that the model is better than a null model.

3.4 Simulation results

Inserting the obtained parameters into the equations indicated in Section 2.6, the total installed wind power capacity for every region and every turbine type in the area under consideration can be computed. Given the prespecified target capacities (cf. Table 5), the remuneration level is iteratively adjusted until these target capacities are reached (cf. Figure 4). The results for the different simulation years are given in Table 5. For the targets of 115 (until 2030), 157 (2035), and 160 GW (2040), compensation levels of 6.09, 7.21, and 8.10 ct/kWh, respectively, are necessary.

Table 5: Capacities and compensations for simulation years

	2030	**2035**	**2040**
Total target installed capacity	115 GW	157 GW	160 GW
Needed compensation for wind energy plants	6.09 ct/kWh	7.21 ct/kWh	8.10 ct/kWh

Figure 5 shows the total installed capacities per turbine type for the simulation year 2040, with Type 4 having the highest share, followed by turbine types 3 and 2. Hence turbines with a capacity of about 3 MW are the most frequently installed. The distribution pattern for the other target years is rather similar.

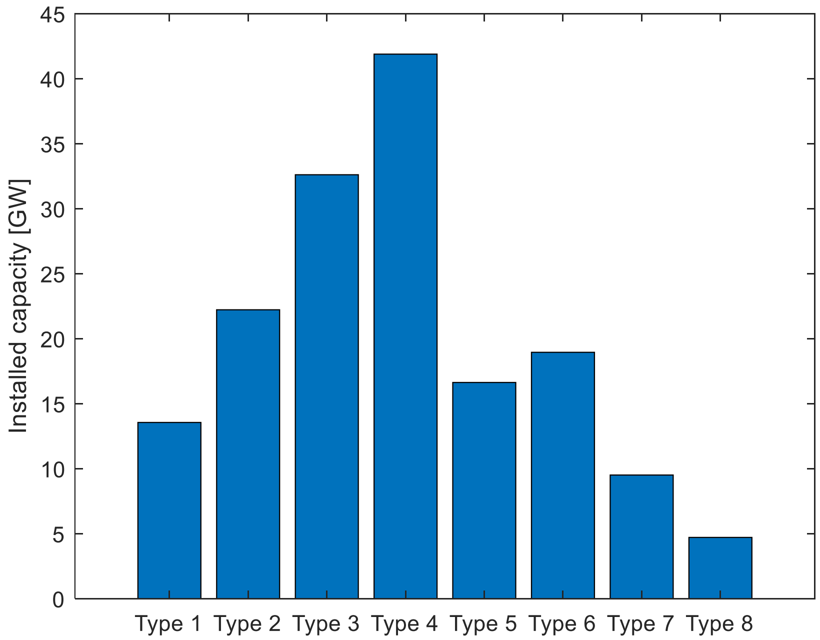

Figure 5: Allocation of installed capacity in the target year 2040 by turbine type

Figure 6 depicts the spatial distribution of the installed capacities per NUTS 3 region in relation to the total area for the base year 2022 and the simulation years 2030, 2035, and 2040. Regions with favorable wind conditions are predominantly situated in the Northern half of the country. The dark blue shading indicates that the expansion of wind energy will continue to be concentrated in these regions according to our model. Densely populated and hilly areas contribute little to the ambitious wind energy expansion. Compared to the base year figures, development in the south yet also accelerates. Over time, the number of regions without installed capacity decreases.

Table 6**Fehler! Verweisquelle konnte nicht gefunden werden.** lists the top 10 regions regarding the toal capacity installed in 2040.. The *capacity to add* indicates the additional capacity that needs to be installed considering a lifespan of 22 years for the turbines in the base year fleet. The exploitation probability of suitable areas for wind energy utilization is determined by dividing the absolute installed capacity by the power potential applied to the suitable area. Results regarding the exploitation probability are illustrated in detail in Figure 7.

Table 6: Top 10 regions regarding installed capacity in 2040

nutsID	city/ district name	Total area [km²]	Capacity total [MW]	Capacity to add [MW]	Capacity per area [MW/km²]	Capacity per available area [MW/km²]	Exploitation probability
DE40I	Uckermark	3077	**3164**	2739	1.03	4.13	0.18
DEF07	Nordfriesland	2083	**2994**	2662	1.44	5.47	0.24
DE80O	Ludwigslust-Parchim	4768	**2914**	2741	0.61	2.59	0.12
DEA34	Borken	1423	**2709**	2553	1.90	11.50	0.51
DE949	Emsland	2884	**2420**	2085	0.84	1.77	0.08
DEF05	Dithmarschen	1442	**2402**	2229	1.67	5.43	0.24
DE80J	Mecklenburgische Seenplatte	5496	**2390**	2362	0.43	2.52	0.11
DEA37	Steinfurt	1796	**2082**	1974	1.16	11.44	0.51
DEE0D	Stendal	2436	**1855**	1764	0.76	3.16	0.14
DE40D	Ostprignitz-Ruppin	2526	**1822**	1820	0.72	3.49	0.16

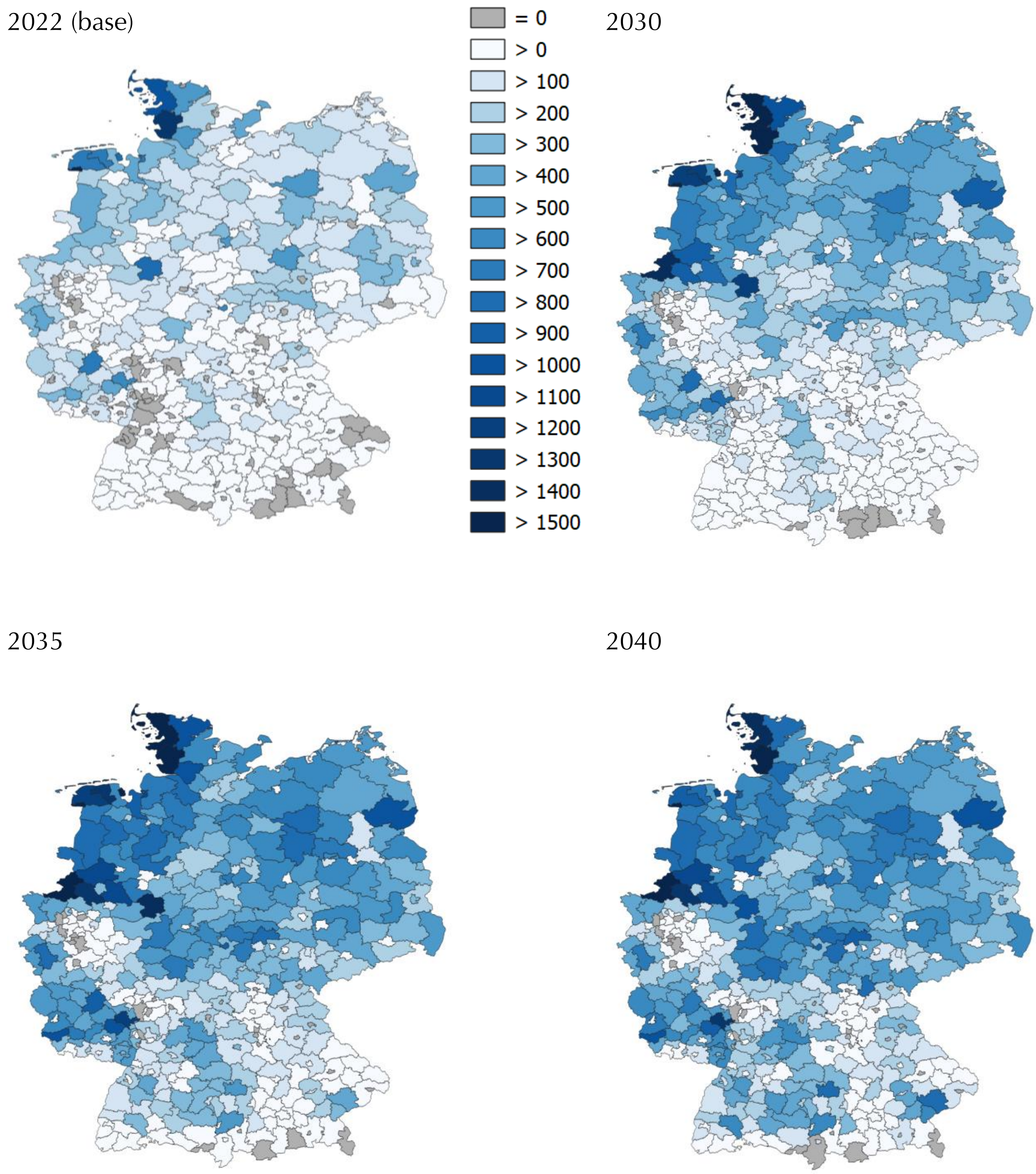

Figure 6: Capacities per total area [kW/km²] per NUTS3 region for the base year, 2030, 2035 and 2040

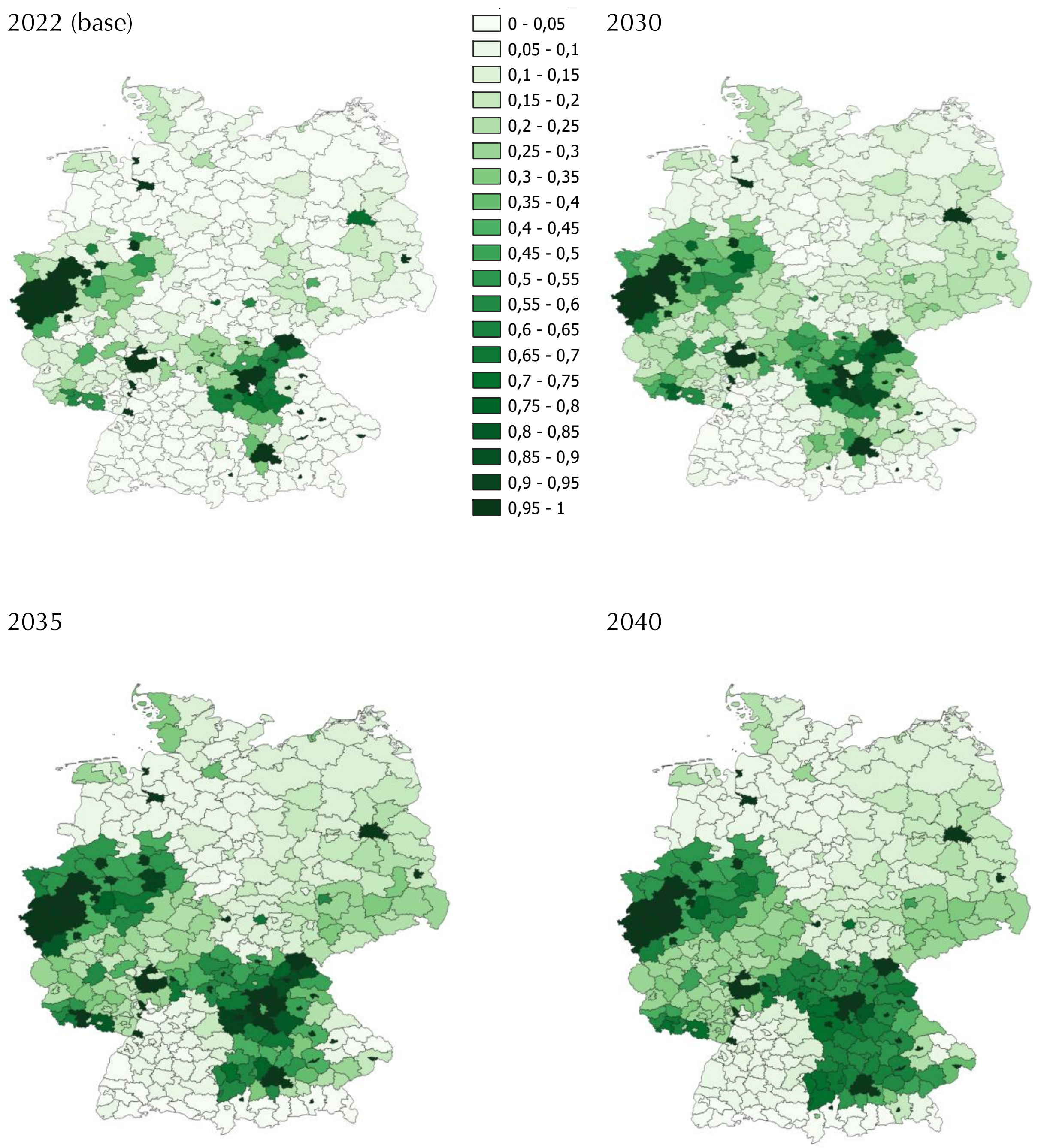

Figure 7: Usage probability of suitable areas per NTUS3 region for the base year, 2030, 2035 and 2040

In Figure 7, regions are colored in dark green if suitable areas are almost fully utilized – either since suitable areas are rare (e.g. in the large cities like Berlin or in the Rhine and Ruhr area in the west) or since a significant portion of the suitable area has already been developed. This seems to be notably the case in important parts of Bavaria (southeast of Germany) as of today – yet this at least partly due to particularly severe state-level regulations regarding minimum distances from wind turbines to settlements.

In Northern and Central Germany, a substantial increase in the utilization probability is observable over the years, but due to high area potentials, the coloration remains in the light green range. In some regions, there is even a decline in relative usage over the course of the years as existing facilities are decommissioned and capacities are relocated based on economic considerations in the context of the incentives set by German regulations.

4 Discussion

The simulation results heavily rely on the area analyses, where determining suitable areas using a consistent method and data is particularly challenging. Spatial planning documents at local and regional levels are neither uniformly available nor based on a comparable time horizon. (Bons, et al., 2023) investigate the availability and usability of designated areas at the municipal and regional planning levels, along with the requirements arising from the planned wind energy expansion. Their findings indicate that legally binding areas, including current proposals and repowering potential, offer less than 30 GW of capacity potential until 2030, which is insufficient to meet the targeted expansion in the upcoming years. They collected and processed data from regional planning and municipal development plans but found that ensuring consistent data quality and completeness is challenging due to the absence of central registries.

Given these challenges, we employed a methodology that enables consistent area determination across the entire country using publicly available data. One backdrop of the approach is that this occasionally results in wind energy facilities installed in identified non-feasible areas in the base year – especially in urban areas. Furthermore, this so-called white area analysis also yields different results depending on the degree of consideration of nature conservation areas and state-specific buffer zone rules. Many studies using a similar method determine significantly more than 2 % of the federal area as non-exclusion areas. The GIS analysis conducted for this paper yields a potential area of 13.5 % of the federal land area; (Lütkehus, et al., 2013) calculate 13.8 % and (Pape & Geiger, 2023) 19.7 %. In order to replicate the actual situation for the wind investors, these areas are scaled to the available area both in the estimation (cf. Section 2.3) and the simulation (cf. Section 2.6) phases based on existing evidence regarding available areas.

We implement different land availabilities in the parameter estimation and investment simulation phases to consider the evolving regulatory landscape. This allows for more tailored predictions for investors taking into account the development of specific areas. While historical analysis provides a useful basis for extrapolating future decisions, it's essential to acknowledge the broader factors that influence new construction dynamics. These include manufacturers' production capacities, project planners' capabilities, current incentive structures, and autoregressive trends. Moreover, a landowner's decision to proceed with a wind power project is contingent upon the land being officially designated as a suitable wind site.

Nested Logit models offer advantages over multinomial models by allowing for the modeling of correlations among similar decision alternatives and accommodating hierarchical decision-making processes. This flexibility leads to better-fitting models, especially when decisions are not independent. In contrast to many conventional models that use simple distribution factors, the economic benefits from the investors' perspective are considered in the proposed methodology.

The parameter describing the power potential per area represents one significant lever regarding wind energy yields and land use. We use here a uniform value of 22.5 MW/km^2, which is a simplifying generalization based on (Matthes, et al., 2018), where a land use of 45 m^2/kW upwards is expected. Their assumed land usage of 8318 km^2 for 178 GW in 2050 and an expected output of 390 TWh with 2200 FLH lead to a very similar average power potential. (LANUV NRW, 2012) points in a similar direction by estimating 10 ha for power plants below 2000 kW and 15 ha for power plants above 2000 kW. It is also noteworthy that energy yields strongly vary between locations, given they depend on the wind speed distribution. By contrast, the power potential is primarily driven by the distances between the turbines as well as the turbine type. Given technological advancements and an accelerated wind energy expansion, we anticipate a future power potential of 25 MW/km^2 (cf. Section 3.2).

5 Conclusion

For planning purposes, notably in grid planning, future investments in onshore wind capacities must be estimated at a fine regional granularity. The main factors in the location choice for wind power plants are the expected revenues, depending on prevailing wind conditions, and the available area in the considered region. The allocation of future wind power capacities is significantly influenced by economic considerations and spatial restrictions. In our novel approach, the economic rationality behind investment decisions is captured by calculating the NPV of potential sites, considering investment costs and expected yields derived from wind speed data and power curves. Suitable sites are determined with a GIS-based area analysis, where infeasible areas like settlement, infrastructure, forest, airport, and nature conservation areas, as well as corresponding buffer zones, are excluded. Suitable land areas are identified at the NUTS 3 level in the present study and are scaled according to federal states' legally required contribution targets. Existing wind power plants are thereby accounted for based on published registry data.

The investment decisions for wind power plants are then modeled using a nested logit model. The hierarchical structure of such models is used to determine (i) the probability of turbine installations in a particular region at the first level and (ii) the probability of installing a specific turbine type at the second level. The model application encompasses a parameter estimation phase and an investment simulation phase. Based on observed investments of the last 10 years, the impact of key drivers like profitability or turbine type on decisions at the upper and the lower level of nested logit models are estimated empirically. For this purpose, a maximum likelihood estimation is performed.

The expected investment decisions for future simulation years are then determined in an iterative process. The relative investment probabilities for each region are multiplied by the available remaining area and the power potential before being added to the existing plant capacities. Each iteration adjusts the offered remuneration rate, resulting in changed regional capacities. This process is repeated until the national expansion target is met.

In an application for the German onshore wind energy expansion targets, the average compensation for the required 115 GW in 2030 is found to be 6.1 ct/kWh. The 160 GW target for 2040 results in a compensation of 8.1 ct/kWh. Due to the prevailing wind conditions, favorable sites are especially located in the northern part of Germany, while urban and hilly areas are found to be less attractive for investments.

This study concludes that a combination of economic efficiency considerations and spatial restrictions critically shapes Germany's future spatial distribution of onshore wind energy capacity. By accounting for historical expansion trends and hierarchical decision-making processes, the nested logit model offers a powerful tool for understanding and predicting regional and turbine-type selection probabilities. These insights are essential for policymakers and investors to strategically plan and implement wind energy projects, contributing to the achievement of Germany's renewable energy targets.

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Appendix A

To assess the robustness of the empirical parameter estimates and the simulation results presented in Section 3, we use weather data from the five years preceding the base year 2022. Hourly wind speed data for each region were extracted and converted into duration curves for each year, which were then averaged. This approach ensures a broader representation of longer-term characteristics of wind availability and variability. Importantly, simply averaging the wind speed corresponding to identical timestamps without prior sorting would yield unrealistic results since such an approach would effectively smooth out periods of high and low wind speeds, misrepresenting the true distribution of wind intensity over time. The results given in Table 7 demonstrate that the derived parameters are consistent with those obtained in the application Section 3. In the simulations, the obtained target remunerations are 6.23 ct/kWh for 2030, 7.20 ct/kWh for 2035, and 7.99 ct/kWh for 2040. These values closely align with the previously derived estimates, confirming the robustness of the developed methodology.

Table 7: Parameter estimation results based on five years of weather data

Parameter	Estimate	Standard Error	t Statistic	
$\boldsymbol{\beta}$	5.3365	0.8203	6.5051	***
$\boldsymbol{\gamma}$	-95.4181	14.6575	-6.5098	***
$\boldsymbol{\lambda}$	1.0137	0.2211	4.5858	***
$\boldsymbol{\alpha_1}$	0.8467	0.3807	2.2239	*
$\boldsymbol{\alpha_2}$	-0.4007	0.2581	-1.5525	
$\boldsymbol{\alpha_3}$	0.5289	0.2156	2.4535	*
$\boldsymbol{\alpha_5}$	-0.8228	0.3085	-2.6668	**
$\boldsymbol{\alpha_6}$	-0.6629	0.3295	-2.0120	*
$\boldsymbol{\alpha_7}$	-0.4988	0.4956	-1.0064	
$\boldsymbol{\alpha_8}$	-0.4826	0.7418	-0.6506	
$\mathbf{R^2}$		0.1774		

*** p<0.05, ** p<0.01, *** p<0.001**

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