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3D statistical mapping of Germany's wind resource using WSWS

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ABSTRACT

The goal of this study was to model Germany's 3D wind resource using the wind speed-wind shear model (WSWS) on a high spatial resolution grid (200 m × 200 m). The model is based on near-surface wind speed data and reanalysis wind speed data. Furthermore, terrain and land use features were used to develop predictor variables for statistical mapping of study area-wide WSWS parameters. This enables the continuous assessment of the meteorological potential between 10 m and 200 m above ground level. The application of different wind turbine-specific power curves allowed the estimation of the technical potential in the range of common hub heights. Based on the estimates of the meteorological and technical potential, the area which is suitable for wind turbine installation (capacity factor $>$ 0.20) was quantified. It was found that the installation of wind turbines is feasible between 6.6% (hub height of 74 m) and 78.9% (hub height of 169 m) of the study area, depending on wind turbine type. It is assumed that the high spatial resolution modeling improves the assessment of Germany's wind resource from local to the national scale. Since the 3D parameterization of WSWS is based on freely available data, the applied methodology is highly portable and can be transferred to other areas around the world.

1. Introduction

Wind turbines are used to convert the kinetic energy contained in the wind first into mechanical and then into electrical energy [1]. Nowadays, wind turbine technology is considered to be matured and the costs of wind energy are low [2]. In many countries, wind energy has the potential to cover large amounts of the current and future electricity demand [3]. From 2001 to 2016, the accumulated globally installed wind power capacity already increased by 2037% from 23,900 MW to 486,790 MW [4]. In 2016, the largest wind energy capacity was installed in China (168,690 MW), the USA (82,184 MW), and Germany (50,018 MW) [4]. And still great efforts are being made for further expanding wind energy to reach the goals of the Paris climate agreement by reducing CO_2 emissions through substitution of conventional energies by renewable energies.

Prior to the installation of new wind turbines, the suitability of an area for utilizing wind energy is assessed by the wind energy potential. It is typically divided into five categories [5]: meteorological potential, geographical potential, technical potential, economic potential, and implementation potential. Out of these potentials, the meteorological potential is the fundamental basis for planning wind turbine projects. It sets the stage for calculating all other potentials. An accurate assessment of the meteorological potential will consequently lead to more concise estimates of the geographical, technical, economic, and implementation potentials. However, the wind resource strongly varies in the 3D space, especially in orographically complex terrain. Furthermore, the low number of wind speed measurement stations in most areas of the world is insufficient to represent the wind speed regimes in-between measurement stations. Thus, one common approach for modeling the wind resource in-between measurement stations is the application of statistical airflow models, which estimate near-surface wind speed (U) based on the spatial correlation between measured wind speed and environmental factors. Since the application of statistical airflow models is time efficient and computationally efficient, it allows for an immediate evaluation of model accuracy [6]. Furthermore, statistical airflow models are applicable at very high spatial resolutions [7].

The main steps in the development of statistical airflow models are [8]: (1) preparation of measured wind speed time series including homogenization, detrending, and measurement height correction, (2) calculation of statistically meaningful U values (e.g. mean, median, or distribution parameters), (3) mapping of environmental factors that potentially influence near-surface airflow, (4) model building by linking airflow characteristics to environmental factors, and (5) application of the statistical model in the study area.

In a number of previous studies, wind resource assessment was based on mapping average wind speed. For example, simple kriging was used to produce a map of annual mean wind speed in the Netherlands at

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Nomenclature

Acronyms

a.g.l.	above ground level
a.s.l.	above sea level
BA	Bavaria
BB	Brandenburg
BE	Berlin
BR	Bremen
BW	Baden-Württemberg
C1	case one: $U_{1000m} \leq 9.0$ m/s
C2	case two: $U_{1000m} > 9.0$ m/s
cdf	cumulative distribution function
D	four parameter Dagum distribution
DA	data availability
DS1	parameterization dataset
DS2	validation dataset
ecdf	empirical cumulative distribution function
HA	Hamburg
HE	Hesse
JSB	four parameter Johnson SB distribution
L	grid cell
LS	Lower Saxony
LSE	least-squares estimation method
MOM	moment method
MV	Mecklenburg-Vorpommern
NRW	North Rhine-Westphalia
PC1	power curve for Enercon E101-E2-3.5
PC2	power curve for Senvion 3.2M-122 NES
PC3	power curve for General Electric GE Wind 2.5
PC4	power curve for Vestas V112-3.45
PC5	power curve for Nordex N117 3.6
PC6	power curve for Enercon E141-4.2
pdf	probability density function
RP	Rhineland-Palatinate
SA	Saxony
SAA	Saxony-Anhalt
SH	Schleswig-Holstein
SL	Saarland
TH	Thuringia
WSWS	wind speed-wind shear model

Symbols

η	aspect (deg)
ψ	absolute elevation (m)
$\widetilde{E}$	median power law exponent
$\widetilde{U}$	median of daily mean wind speed (m/s)
$\overline{U}$	average of daily mean wind speed (m/s)
a	learning rate
B	weak learner
cf	capacity factor
E	power law exponent
EX	percentage number of exceedances (%)
f	probability density function
F	cumulative distribution function
h	height a.g.l. (m)
m	model
M	total number of weak learners
MAE	mean absolute error (m/s)
MSE	mean squared error (m/s)
P_W	wind turbine power output (W)
$P_W(U)$	wind turbine power curve (W)
R^2	coefficient of determination
$RMSE$	root mean square error (m/s)
u	zonal wind vector component (m/s)
U	wind speed (m/s)
v	meridional wind vector component (m/s)
WTA	wind turbine area (km^2)
X	predictor variable
Y	target variable
$\hat{Y}$	prediction of target variable
z_0	roughness length (m)
α	first Dagum shape parameter
β	Dagum scale parameter
γ	first Johnson SB shape parameter
δ	second Johnson SB shape parameter
ε	second Dagum shape parameter
λ	Johnson SB scale parameter
μ	Dagum location parameter
ρ	copula parameter
ξ	Johnson SB location parameter
τ	orographic sheltering (deg)
φ	curvature (deg)
Φ	relative elevation (m)

Subscripts

1	case one: $U_{1000m} \leq 9.0$ m/s
1000 m	1000 m a.g.l.
100 m	100 m a.g.l.
10 m	10 m a.g.l.
160 m	160 m a.g.l.
2	case two: $U_{1000m} > 9.0$ m/s
60 m	60 m a.g.l.
ar	area
C	copula
ci	cut-in
co	cut-out
dir	direction
g	near surface
h	height
hub	wind turbine hub
i	pressure level
JSB	Johnson SB
k	radius
l	local
p	population
pred	prediction
q	accounting for C1 and C2
r	rated output
z	index of predictor variable combination
zz	index of averaged predictor variable combination

10 m above ground level (a.g.l.) based on wind speed measurements and roughness information [9]. The statistical wind field model of the German Meteorological Service was built by applying multiple regression techniques that require the use of terrain and land use features as predictor variables [10]. However, maps of average wind speed or average wind power density describe only central tendencies of wind speed distributions. A more precise wind resource assessment can be achieved by mapping the parameters of wind speed distributions. Therefore, the ensemble learning method Random Forests was used to estimate Weibull parameters of wind speed distributions on a

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