12.11.2025 - Windenergietage

Enhancing CFD practices for site assessment through polynomial surrogates for estimating uncertainty

Bernhard Stoevesandt, Zahra Lakdawala, Hassan Kassem, Jonas Schulte

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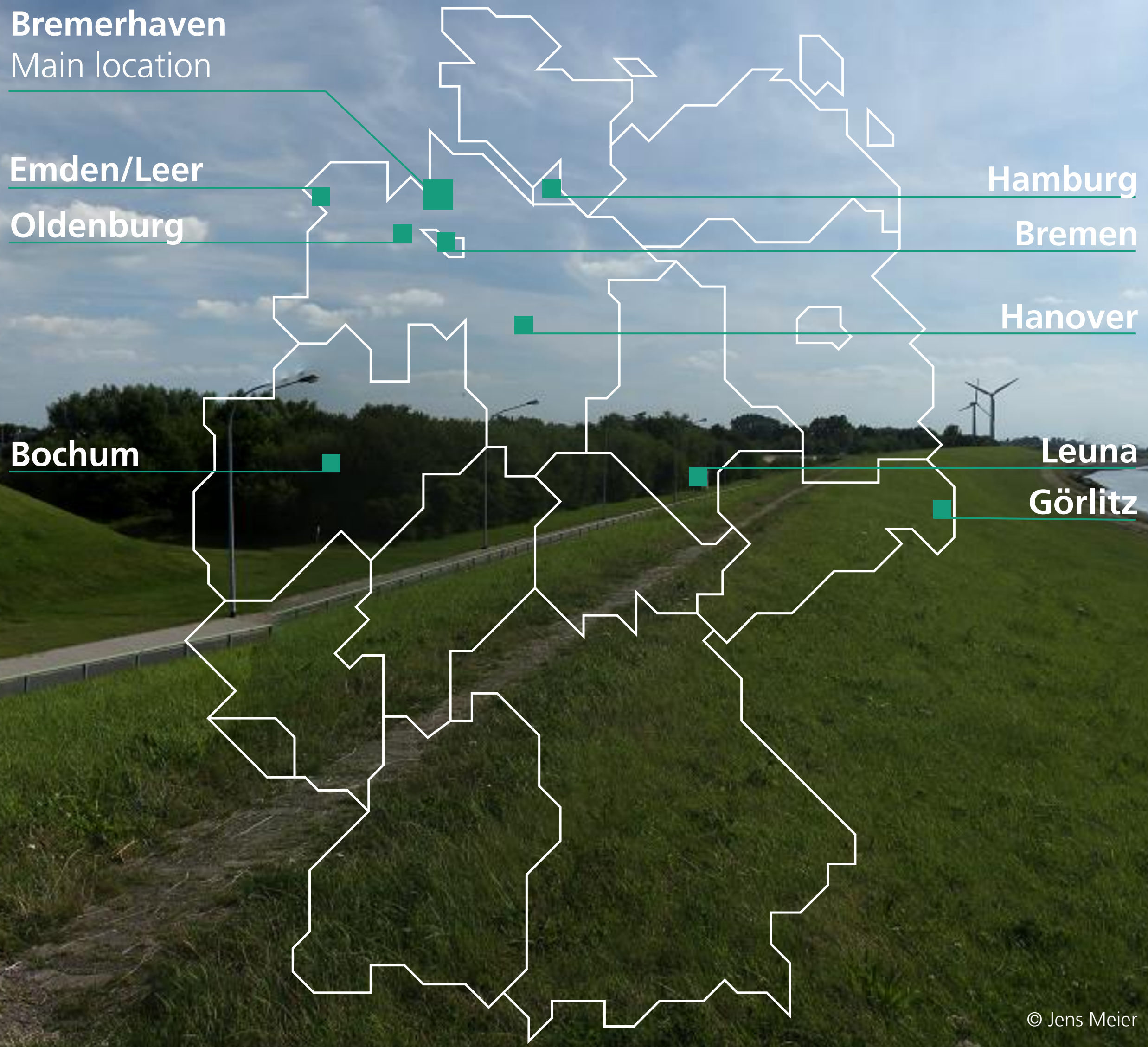

- 400 staff
- 82 publicly funded research projects
- € 45.5 m operating budget / year 2024

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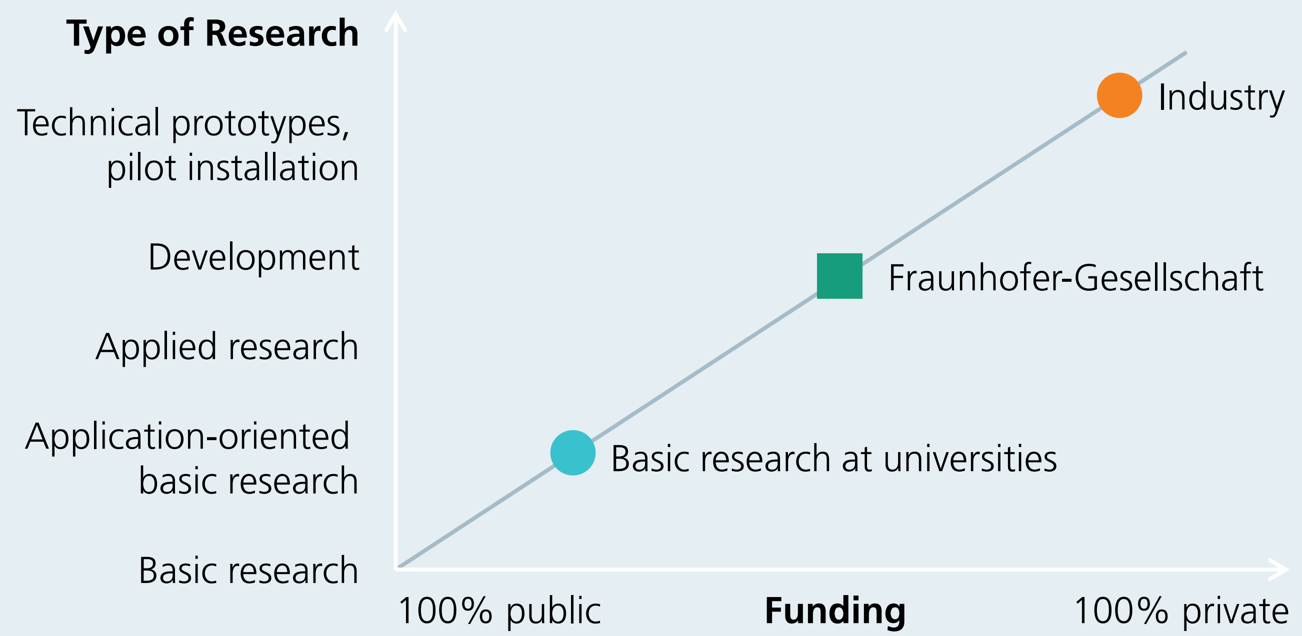
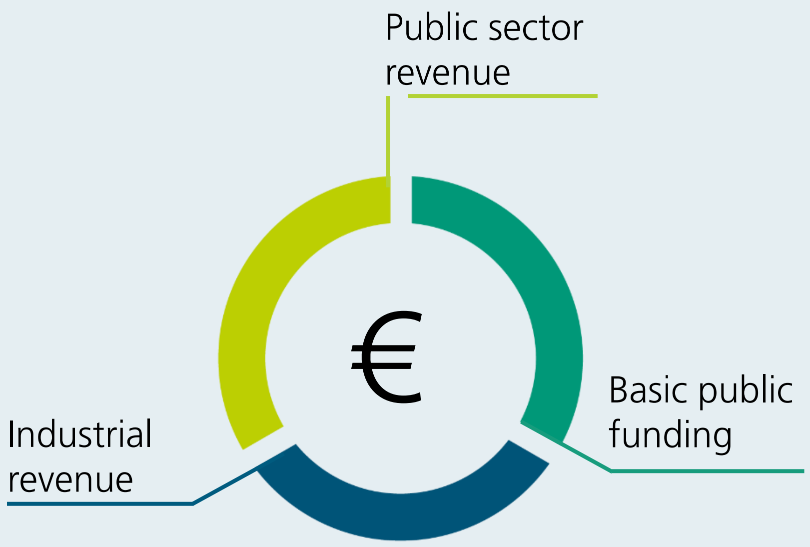
Research with added value for the industry

Fraunhofer-Gesellschaft´s business model





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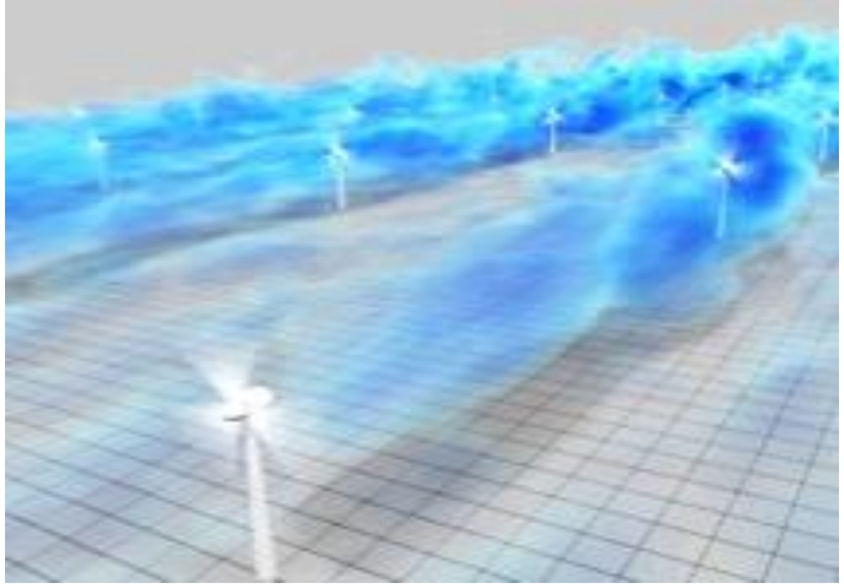
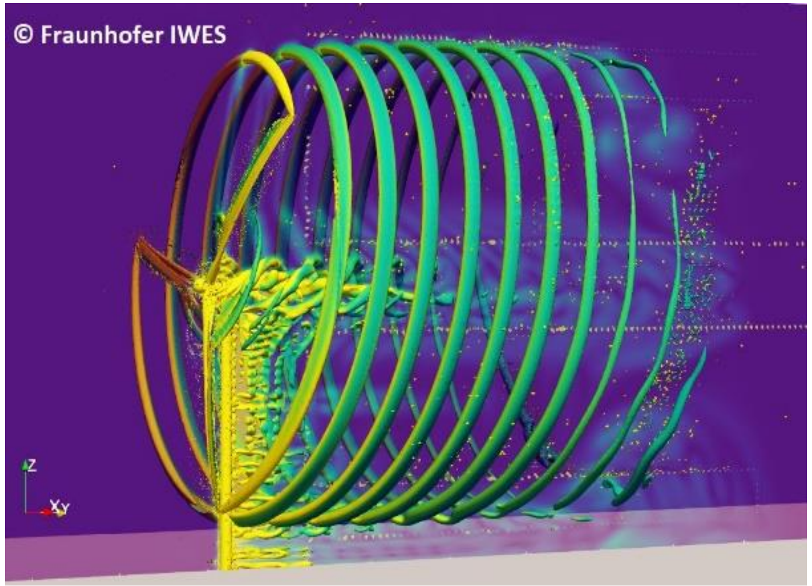
Where are we headed?

Wind environment is uncertain

“research, develop and generate industry suited tools for the evaluation of wind farm yields and sites!”





VISION

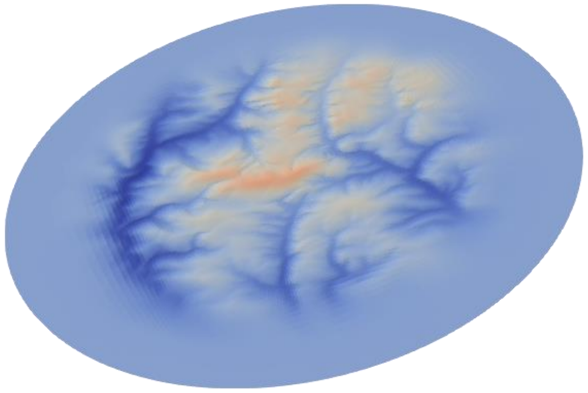
Optimize wind power potential
With minimal risks in resource assessment

- ❑ **Microscale CFD Modeling with Lynxes**
- ❑ Uncertainty Quantification
  - ❑ Polynomial Surrogate
- ❑ Takeaways

What you see is what you get?

Wind environment is uncertain so results need uncertainty

- Uncertainty of wind
  - affects the accuracy in determining the wind energy yield and performance of wind farms
- Wind farms are now increasingly being set up on complex terrains, in forests and hilly areas
- Detailed information is needed on site quality from the early stages of planning



Information on the site quality and possible energy yields of a wind farm (in planning) can only be ascertained with the aid of simulations

State of the art wind simulation toolchain

Localized Yield and Numerical eXloration of Environment and Site (LYNXES)

Complete toolchain for CFD wind resource assessment

Pre-processing
- Forest mapping
- Precursor runs
- Automesher
- Refinement

terrainMesher

Python3 interface

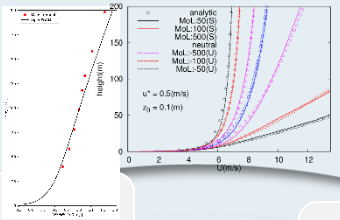
Webapp GUI

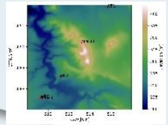
High fidelity models
- Thermal stratification
- Forest modeling
- Forest parameterisation

OpenFOAM-v2306

Post-processing
- Profiles
- Surface extraction
- Time series analysis

Vtk file formats

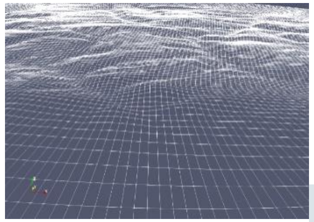




- Microscale CFD Modeling with LYNXES
- **Uncertainty Quantification**
  - Polynomial Surrogate
- Takeaways

Simulation framework

Simulations are plagued with uncertainty



Input:
Numerical parameters
Model parameters
Boundary Conditions
…

- Forest height
- Mesh resolution

Computational model
+
Transfer functions
(solvers)

FIWIND-OpenFOAM

Output:
Fields of interest

- Wind speed U
- Pressure p
- k
- ϵ

$$
\begin{aligned}
\frac{\partial U_j}{\partial x_j} &= 0 \\
\rho\frac{\partial U_i U_j}{\partial x_j} + \rho\frac{\partial < u_i' u_j' >}{\partial x_j} + \frac{\partial}{\partial x_j}(\mu\frac{\partial U_i}{\partial x_j} + \frac{\partial U_j}{\partial x_i}) + \frac{\partial P}{\partial x_i} &= F_i \\
\rho\frac{\partial k}{\partial t} + \rho\frac{\partial U_j k}{\partial x_j} - \frac{\partial}{\partial x_j}[(\mu + \frac{\mu_t}{\sigma_k}\frac{\partial k}{\partial x_j})] &= P_k - \rho\epsilon + S_k \\
\rho\frac{\partial \epsilon}{\partial t} + \rho\frac{\partial U_j \epsilon}{\partial x_j} - \frac{\partial}{\partial x_j}[(\mu + \frac{\mu_t}{\sigma_\epsilon}\frac{\partial \epsilon}{\partial x_j})] &= P_k + \frac{\epsilon}{k}(C_{\epsilon 1}P_k - C_{\epsilon 2\rho\epsilon}) + S_\epsilon
\end{aligned}
$$

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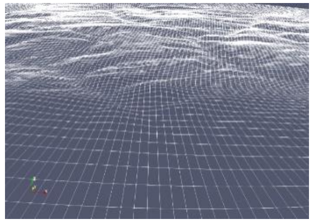

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Awareness of uncertainty factors and their influence is essential for simulation results to be usable!

Simulation framework

Sources of uncertainty – CFD is just physics? Isn't it?

Input:
Outer Wind
Forests characteristics
Terrain characteristics
Mesh discretization
All with uncertainty

Computational approach:
Turbulence model
Computational accuracy
Convergence rate
Numerical accuracy

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Can be tuned to work with a specific accuracy under defined conditions

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Is as good as you get it, or might even change over time
Mesh is a question of computational costs

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Turbulence model
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Putting on the stochastic hat

Monte Carlo Method for uncertainty propagation

Typically, to understand the influence of uncertainty would require solving for multiple cases using the CFD simulation

Forest height
[5-25]m

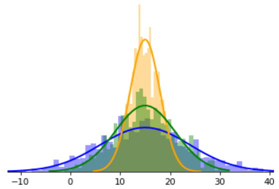
$$v^{(0)}, v^{(1)}, \ldots, v^{(N-1)}$$

Computational model
+
Transfer functions
(solvers)

$$U^{(i)}, V^{(i)}, W^{(i)}, k^{(i)}, \varepsilon^{(i)}, \ldots \; .$$

$$p(v) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{v - v_0}{\sigma}\right)^2\right]$$

$$\int_{-\infty}^{\infty} p(v) \, \mathrm{d}v = 1$$



For each resulting field, the set of N simulations can be interpreted as discrete values of a **continuous function** of random variable v

$$U(v), V(v), W(v), k(V), \varepsilon(v), \ldots$$

MONTE CARLO:

- ❑ Define a domain of possible inputs
- ❑ Generate inputs randomly from a <u>probability distribution</u> over the domain
- ❑ Perform a <u>deterministic</u> computation on the inputs
- ❑ Aggregate the results to form a probability distribution for the output fields.

Monte Carlo methods require large amounts of random inputs!

Putting on the stochastic hat

Can we have an output distribution with less random inputs and outputs?

Forest height
[5-25]m

$v^{(0)}, v^{(1)}, \ldots, v^{(N-1)}$

Computational model
+
Transfer functions
(solvers)

$U^{(i)}, V^{(i)}, W^{(i)}, k^{(i)}, \varepsilon^{(i)}, \ldots$.

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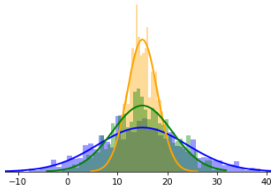

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Monte Carlo methods require large amounts of random inputs!

Propagate input uncertainty through computational methods

Method 2: Non-intrusive polynomial Chaos Expansion

PCE defines a relationship between input and output (CFD field) via a function that is a linear combination of some orthogonal functions on which input is projected upon

$$\xi(v) = \frac{v - v_0}{\sigma}$$

POLYNOMIAL CHAOS EXPANSION

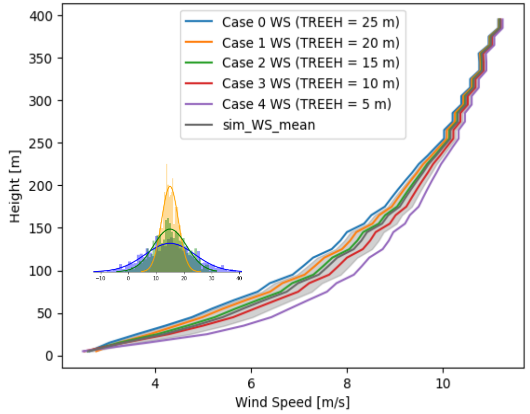
$$\widehat{U}(\xi) = f((\xi) = \sum_{n=0}^{\infty} \alpha_n \varphi_n(\xi)$$

$$\hat{U}(\xi) = U(v(\xi))$$

Gaussian Input variable (forest height)

CFD output (wind speed)

- Only a small number of CFD simulations are required
- Solves a linear system on every cell
- Results in the variance of CFD field output in every point
- Implemented a python package



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Non-Intrusive Polynomial Chaos Expansion

In a nutshell

5 (or more) CFD results, varying one input parameter

Input parameter distribution type: Gaussian or uniform

Input parameter distribution mean and width

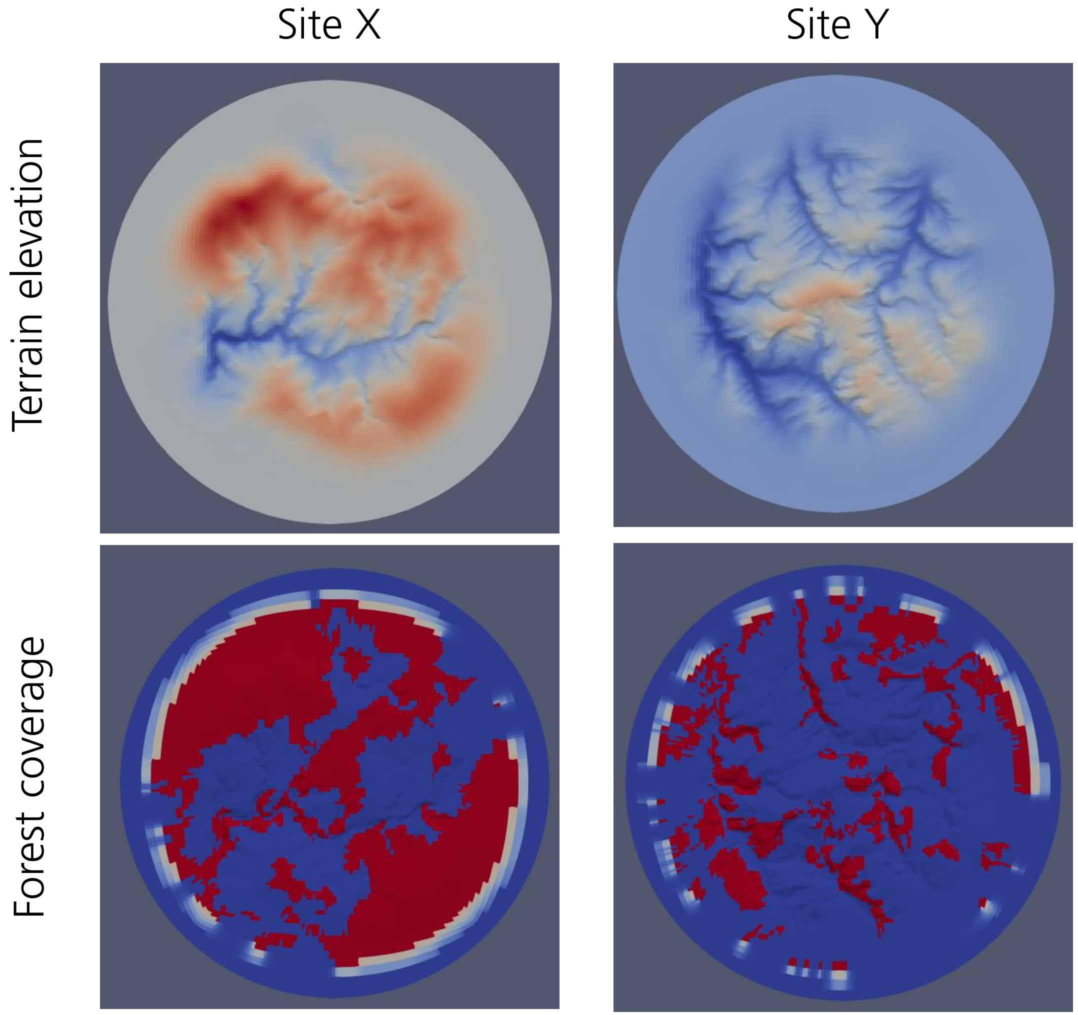
PCE

Mean, variance and other distributional moments of all CFD fields in all mesh cells

- PCE mainly avoids large Monte-Carlo samples
- We applied PCE to unknown
  - Forest height
  - Mesh resolution
  - Thermal stability

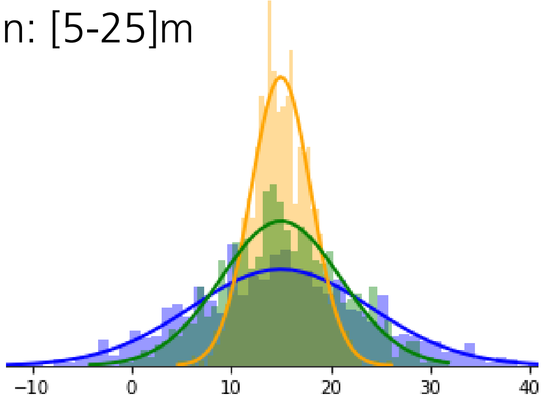
Forest height impact on wind speed

How is uncertainty in forest height propagated into wind speed calculations



- Sites with height variation of about 500-2500m
- Fixed mesh resolution
- Showing two, but actually tested on more sites

- Overlay a forest canopy model for constant LAD 0.07
- Forest height variation: [5-25]m

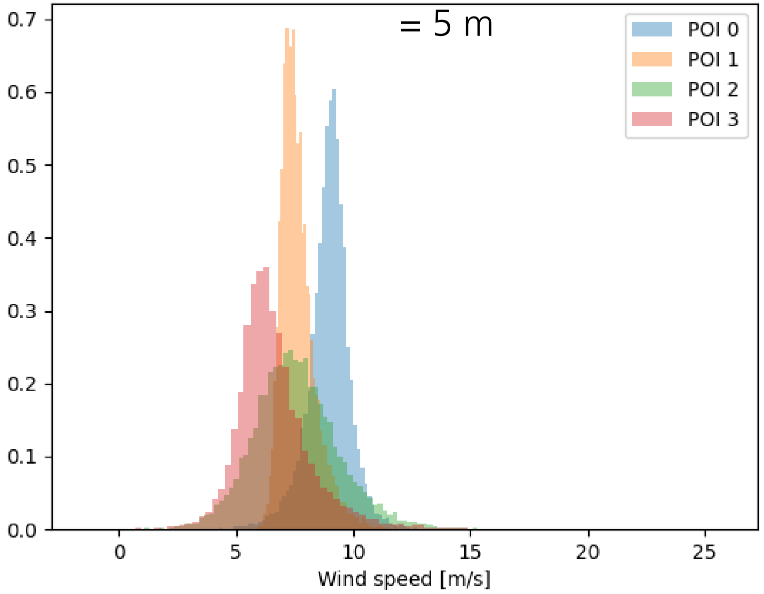


Forest height variability

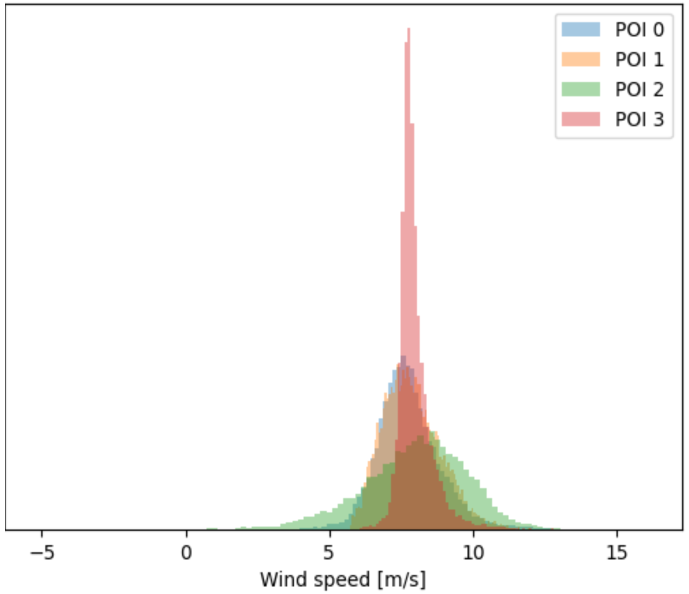
Site: Nussbach, Germany.

In each cell of the mesh, we can reconstruct the distribution of CFD results, given the variability of the input parameter.

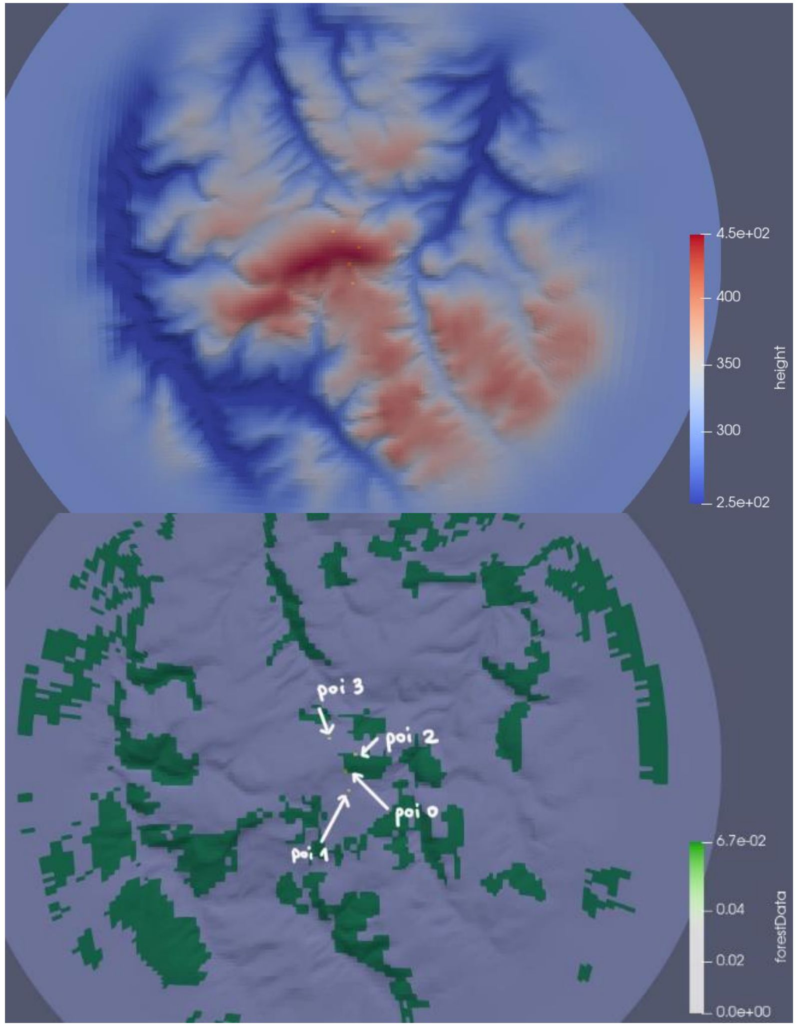
Forest height: Gauss distributed, 15 m, sigma = 5 m



Wind direction: 135 degrees



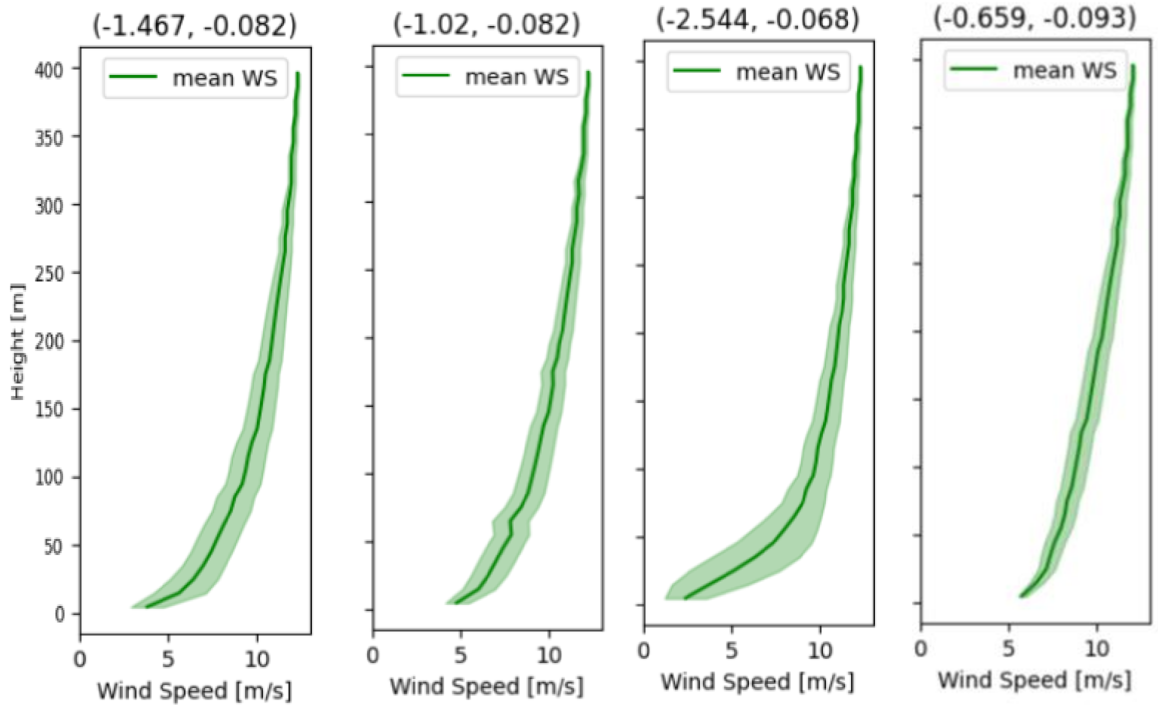
Wind direction: 225 degrees

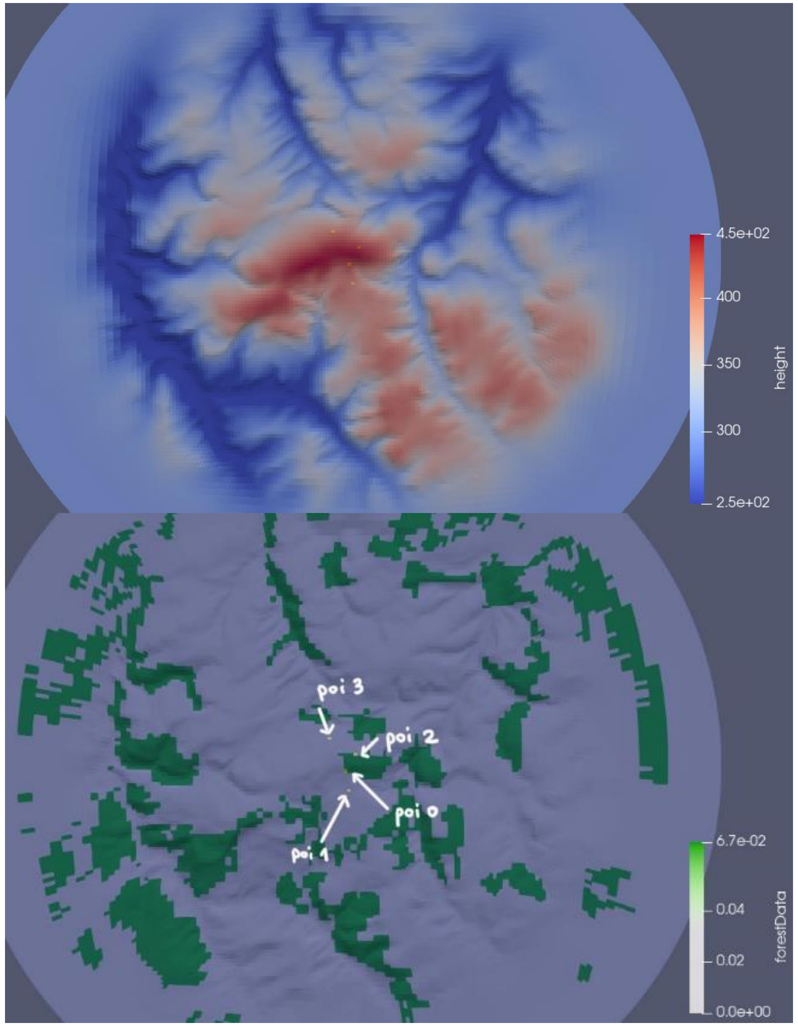


Forest height variability

Site: Nussbach, Germany. Wind direction: 225 degrees

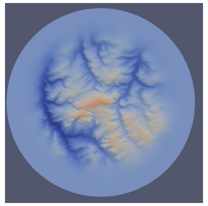
Furthermore, uncertainty bands can be calculated for vertical profiles at the points of interest

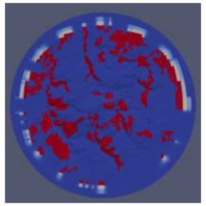


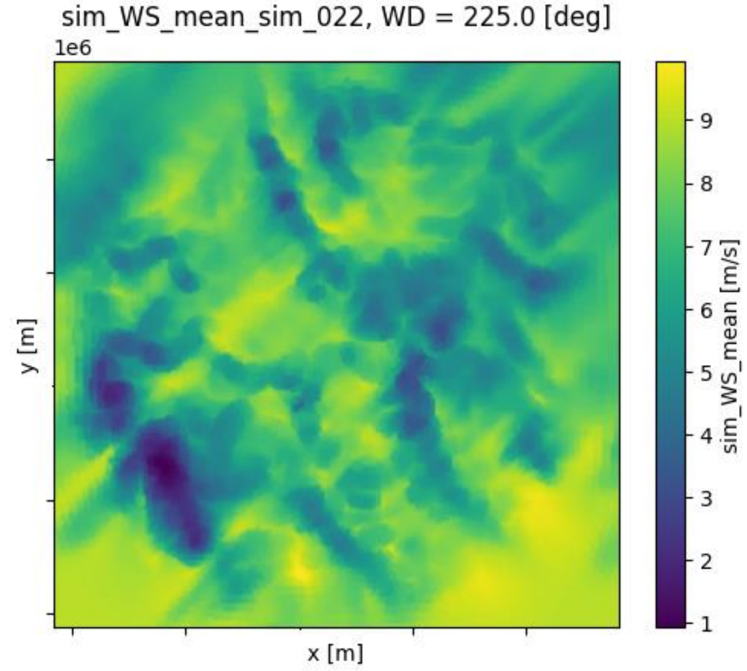


Wind speed and wind speed variability for Site Y

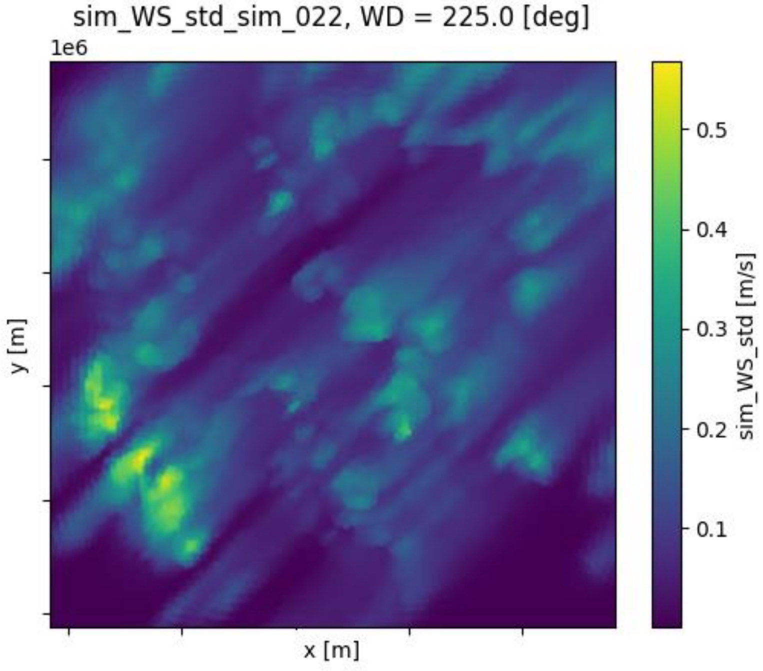
At a fixed height of 50m



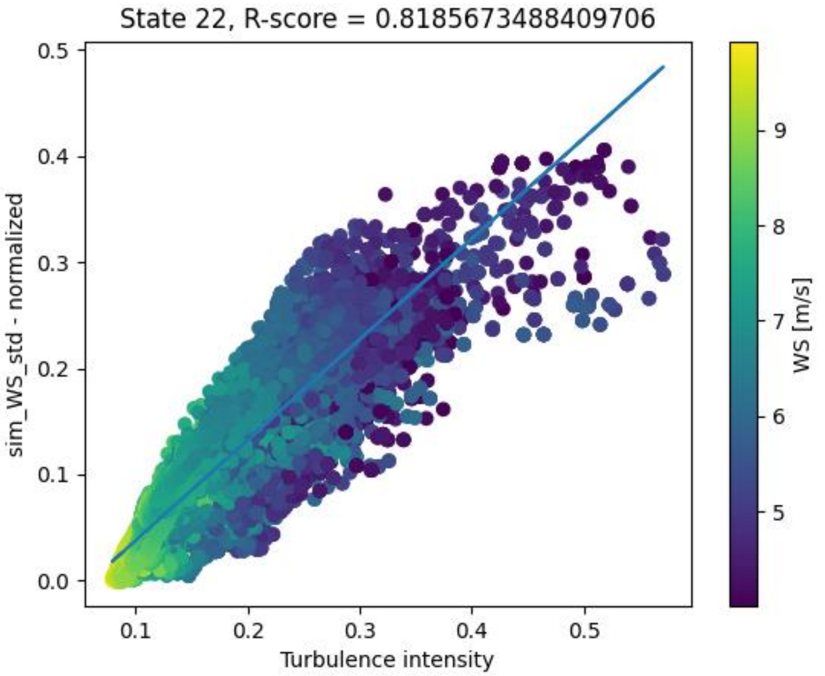




Wind speed computed via CFD simulations



Standard deviation in wind speed computed via PCE



Takeaways

Magnify uncertainties in CFD – Yes, we can

- Even though CFD is a deterministic approach uncertainties can be quantified
- Several sources for uncertainties exist
- Different methods can be chosen to quantify
- The polynomial chaos expansion is a unique approach reducing the computational costs strongly
- Works for several aspects of input parameters
- Can be used in any CFD toolchain – we use an OpenFoam based toolchain

Contact

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Polynomial Chaos Expansion

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$$\hat{U}(\xi) = U(v(\xi))$$

Gaussian Input variable (forest height)

CFD output (wind speed)

- What is $\varphi_n(\xi)$?
  - a special choice of orthogonal basis function (Hermite polynomial function)

$$\hat{U}(\xi) = \sum_{n=0}^{\infty} \alpha_n H_n(\xi)$$

  - If ξ is sampled from other distributions, then $H_n(\xi) = \varphi_n$ are different choice of basis functions

