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Exploring the Interdependence of Vertical Extrapolation Uncertainties in Repowering Wind Farms

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INTRODUCTION

Assessing a wind farm's annual energy production (AEP) involves using a physics-driven model (PDM). By adjusting and combining this PDM with historical power records of the existing farm, we can improve the accuracy of energy yield assessments for a repowered farm [1]. This process includes running the PDM for both the existing and repowered farms using the same wind data input, specifically from the existing farm's development mast, eliminating the need for a new measurement campaign.

In a Monte Carlo framework, this involves considering the input uncertainty distributions for both wind farms and their potential correlation. The uncertainty samples for both farms must reflect a certain level of correlation due to their common origins. For instance, using the same mast data implies that the measurement uncertainty samples are identical for both farms. Figure 1 depicts a process of sampling bivariate distributions.

Correlation of uncertainty for the vertical profile modeling have not been investigated however repowered farm turbines are generally taller than existing farm turbines. Therefore, the joint Monte Carlo simulation of the production model for both farms must account for the uncertainty in vertical extrapolation, which intuitively includes a certain level of correlation. This work demonstrates that the bivariate structure of the power law model [2] is Gaussian with correlation values ranging from 82% to 97%.

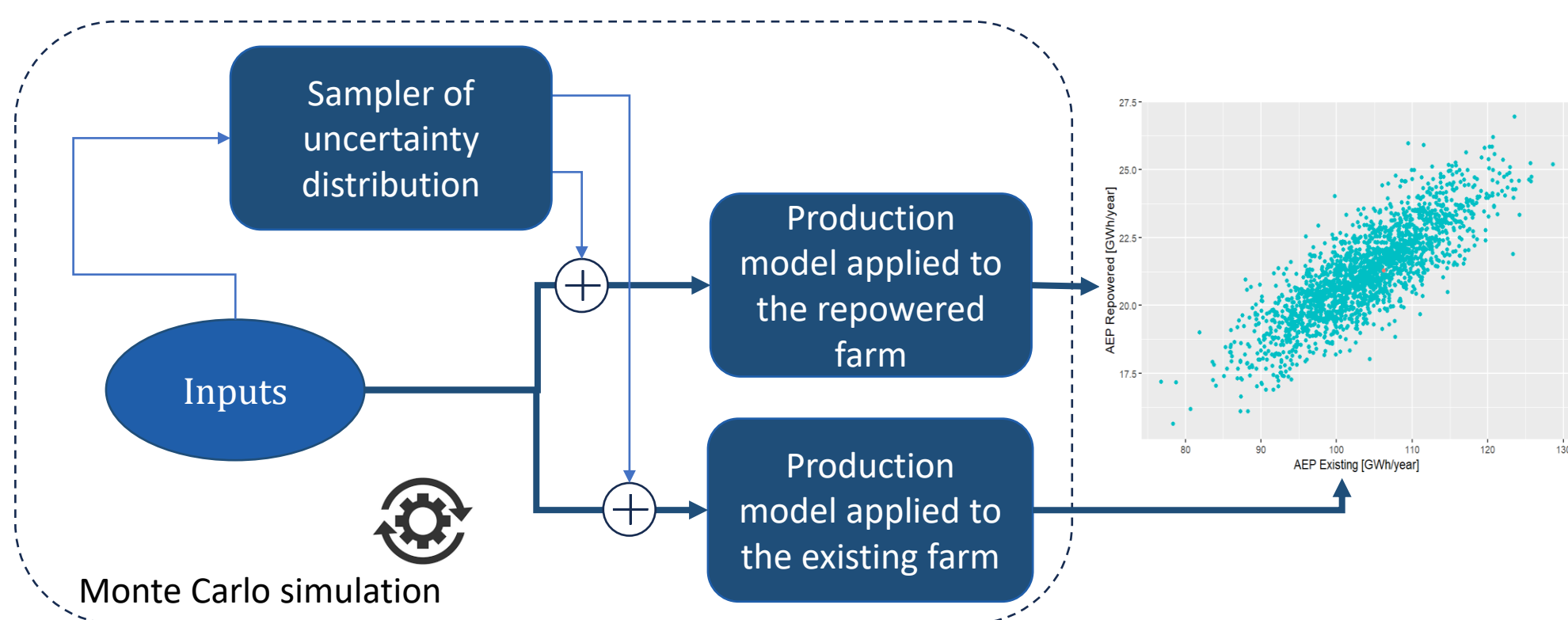


Fig 1. The Monte Carlo scheme for assessing the energy yield of a repowered farm, along with an example graph of the sampled bivariate distribution of energy production. The identified correlation model is used in the "sampler of uncertainty distribution" block.

METHOD

Power law extrapolates the wind speed at hub heights either for the existing or repowered farm (see h_e and h_r on figure 2), using two wind measurements at lower heights (see h_1 and h_2 on figure 2). The error is the difference between the mean modelled wind speed (see U_e and U_r on figure 2) and the mean real wind speed over a multi-month period:

$$\Delta U_e = U_e - U_{real}(h_e)$$

$$\Delta U_r = U_r - U_{real}(h_r)$$

The method to investigate the uncertainty distribution consists of:

1. Regression of a model f that explains the error based on the shear coefficient and the ratio of heights. The regression minimizes the residuals ξ :

$$\frac{\Delta U}{U} = f\left(\frac{h}{h_2}, \alpha\right) + \xi \text{ with } h \in \{h_e, h_r\}$$

2. Model the cumulative distribution function (C.D.F.) F of the residuals ξ ,
3. Obtain a dataset of transformed residuals $\{F(\xi_e), F(\xi_r)\}$ using (ξ_e, ξ_r) for each pairs of observed errors (see Figure 3),
4. Identify the best matching copula C [3] to the dataset $\{F(\xi_e), F(\xi_r)\}$.

Sampling of the uncertainty distribution follows the inverse path: sampling of the residuals from the copula C , transformation using the inverse C.D.F.s F^{-1} to obtain two joint samples of the residuals, addition of the bias terms to obtain joint samples of the error ($\Delta U_e, \Delta U_r$), and finally, repetition of this operation to obtain a representative sampling.

DATASET

The experimental dataset consists of 12 wind measurement campaigns at different locations in France, covering from 4 to 12 months. The sites range from simple to moderately complex and include patches of forests close to the device. Data were quality-checked using expert-based visual analysis. The real wind speed U_{real} is the measurement. The lower heights are used to model the upper heights wind speeds U : figure 3 depicts this process. Depending on measurement devices, multiple combinations of heights are available (up to 100 for a Lidar). Finally, the dataset contains 843 observed errors.

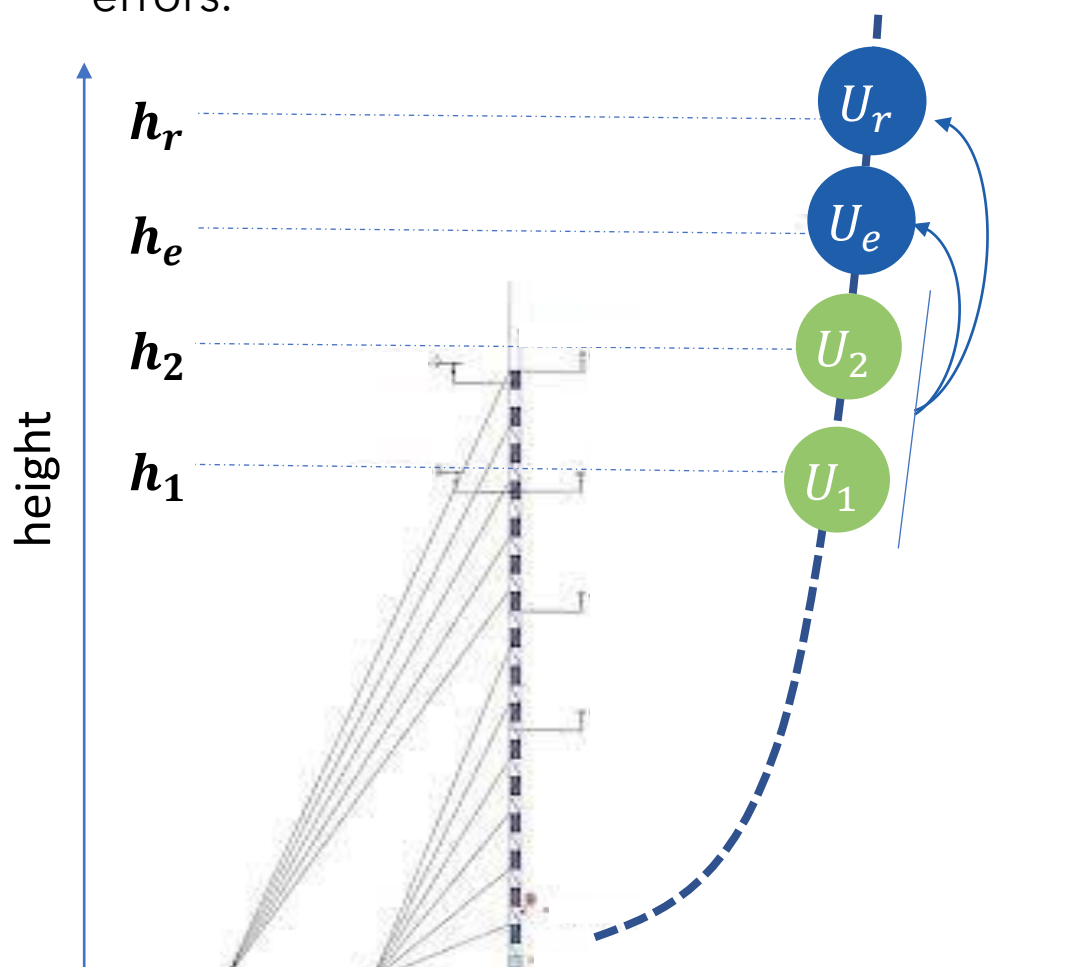


Fig 2. Vertical extrapolation for repowering project: the mast measurement are extrapolated at heights of interests for both the existing and repowered farms

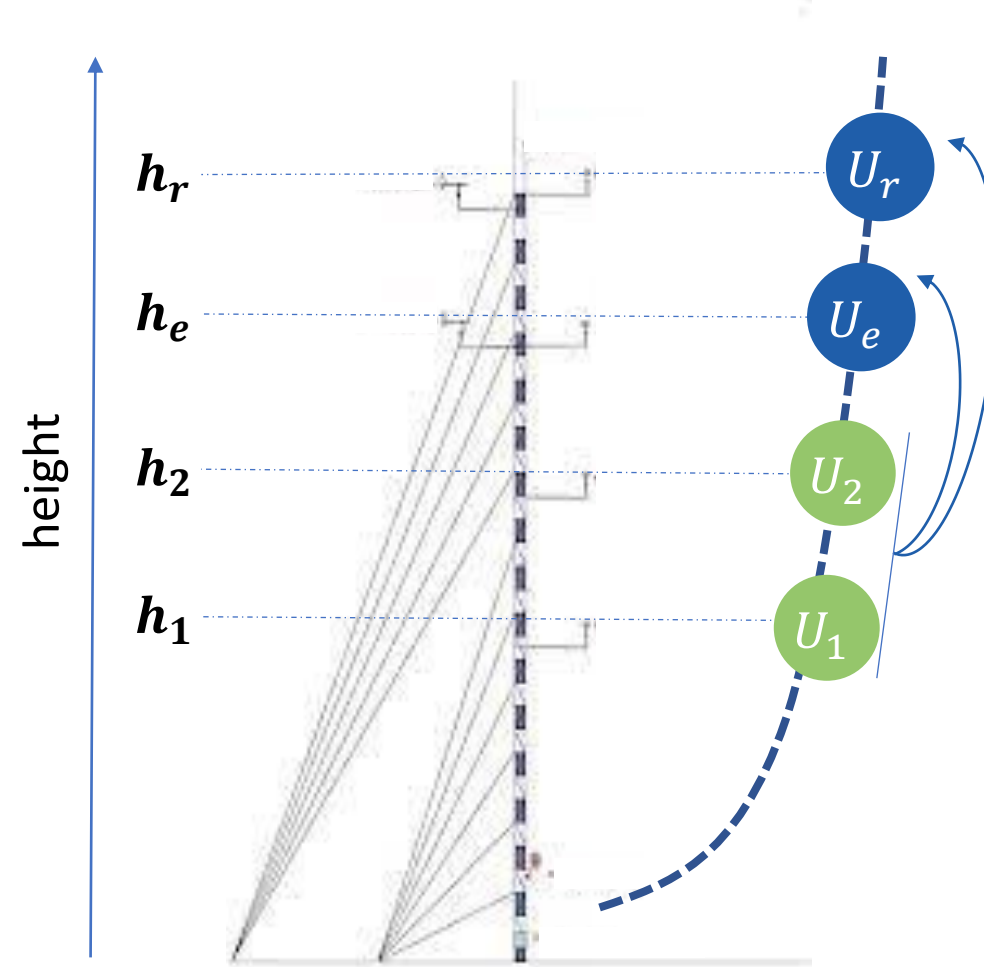


Fig 3. Method to observe power law model errors: the extrapolated wind speed are compared to upper heights measurements.

UNIVARIATE DISTRIBUTION OF POWER LAW MODEL ERROR

Figures 4 and 5 show the relationship between the error and the atmospheric (shear) and farm (ratio of height) parameters. There is a linear trend for the latter and a noisy linear trend for the former. A bi-linear model captures the influence of these parameters on the error. It achieves a determination coefficient (R2) of 60%:

$$f\left(\frac{h}{h_2}, \alpha\right) = 0.06 - 0.05 * \frac{h}{h_2} - 0.30 * \alpha + 0.27 * \frac{h}{h_2} * \alpha$$

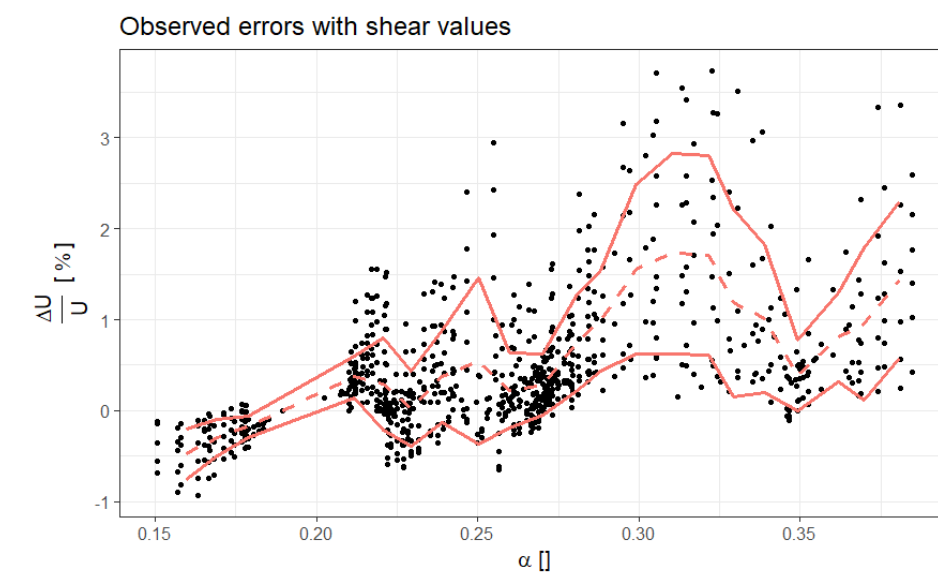


Fig 4. Scatter plot of error vs shear coefficient. Dashed line is the mean error and full lines represent the 1-sigma interval.

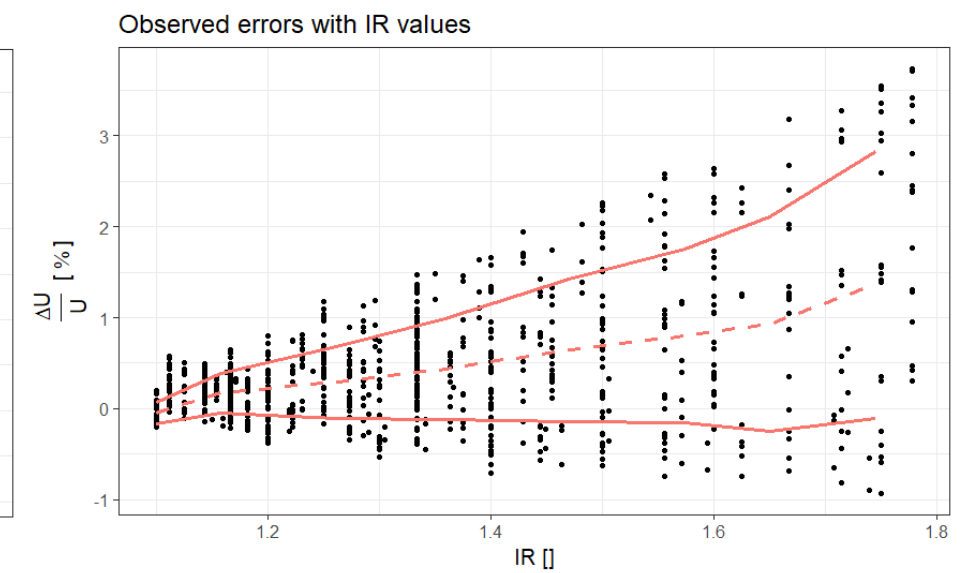


Fig 5. Scatter plot of error vs the inter-range ratio (IR) defined as h/h_2 . Dashed line is the mean error and full lines represent the 1-sigma interval.

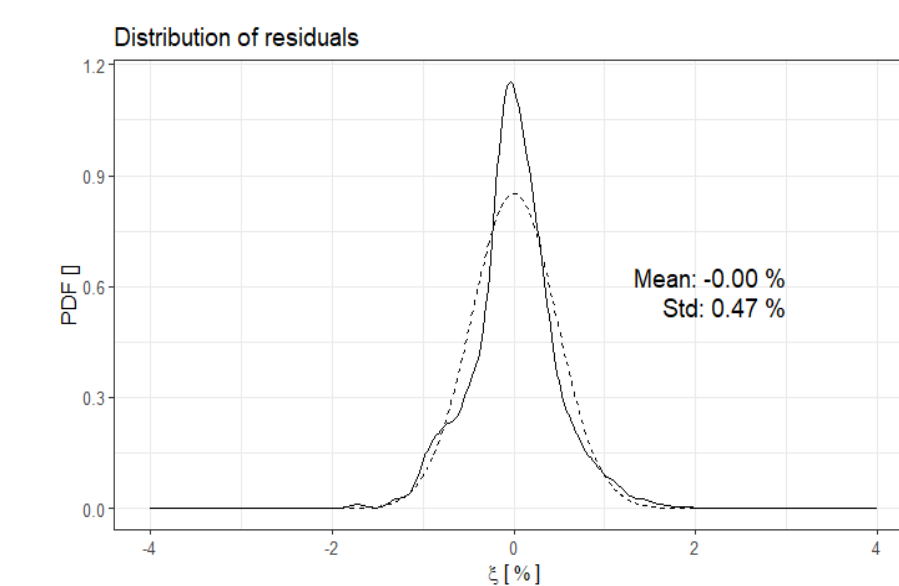


Fig 6. The experimental probability density function of the residuals (full line) and the best Gaussian fit (dashed line).

Figure 6 shows the distribution of the residuals along with the best Gaussian fit:

$$\xi = \frac{\Delta U}{U} - f\left(\frac{h}{h_2}, \alpha\right)$$

The residuals have a null-mean Gaussian distribution with a standard deviation of 0.47%. A Shapiro normality test achieves a p-value of 10% and further confirms that the distribution is likely Gaussian. The standard deviation is modeled using the model of [4]. A calibration using the maximum likelihood estimation approach confirmed the parameters found in [4].

BI-VARIATE DISTRIBUTION OF POWER LAW MODEL ERROR

C.D.F. transformation consists of applying the C.D.F. F to the residuals ξ : the resulting set $\{F(\xi)\}$ is uniformly distributed over $[0,1]$. This allows the fit of a copula C independently of the marginal distribution. Figure 7 shows the pairs of transformed power law modeling error: there is a clear linear correlation with a slight asymmetry. The Gaussian copula C provides the best Akaike Information Criterion [5] value on the dataset: the Gaussian copula best fits the power law modeling error. Given that the marginal and the Copula are Gaussian, Sklar's theorem states that the bivariate distribution is Gaussian. The correlation coefficient parametrizes this distribution. To reflect the decrease of coherence with height, we categorize the projects with the height ratio h_r/h_e . For a height ratio less than 1.2, the coefficient is 97%. It is 90% for a ratio between 1.2 and 1.4 and 82% for a ratio between 1.4 and 1.6.

CONCLUSION

The Gaussian distribution effectively characterizes the bi-variate structure of errors in power law modeling. As anticipated, the correlation between modeled and observed values diminishes with increasing height, ranging from a correlation coefficient of 97% at proximate extrapolation heights to 82% at more distant heights. Regarding the marginal distribution, power law modeling errors exhibit increasing bias and variance with greater shear and extrapolation heights. This model's applicability is limited to simple terrain and typical Western European climate conditions. Figure 8 illustrates the uncertainty sampling in vertical profile modeling for a wind farm repowering scenario: despite the high correlation, the scatter plot reveals significant dispersion, indicating a non-negligible probability of observing errors with different magnitudes or opposite signs.

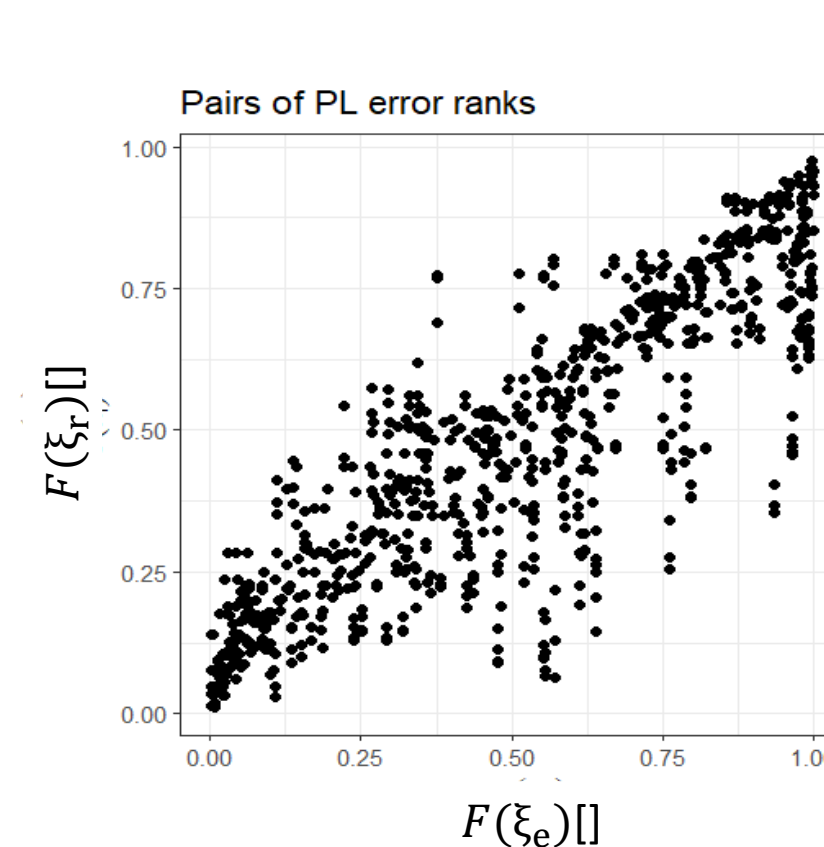


Fig 7. Observation: scatter plot of the transformed residuals using the C.D.F. F

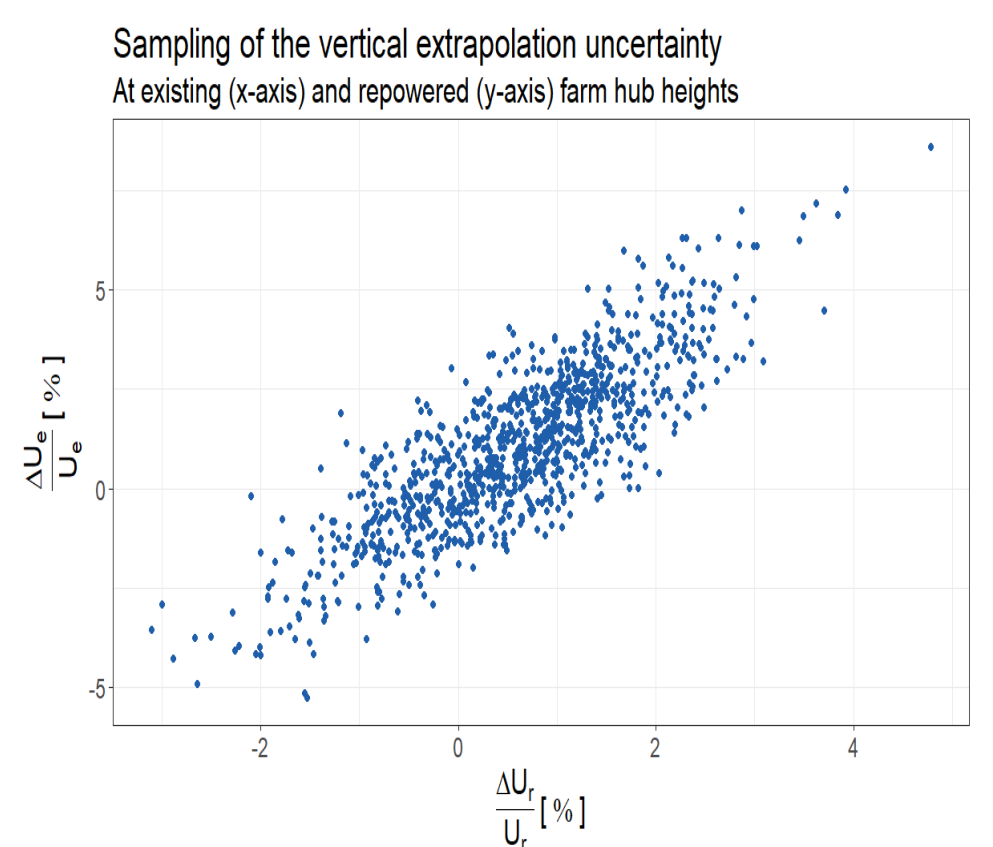


Fig 8. Simulation: sampling of power law errors for existing and repowered farms of 60 and 100 meters hub heights, a mean shear coefficient of 0.2 and a 40 meters mast. It includes a 1% measurement uncertainty.

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