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## Applying triple collocation for verifying wind resource measurements and reanalysis data

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# Overview

## Agenda of this presentation

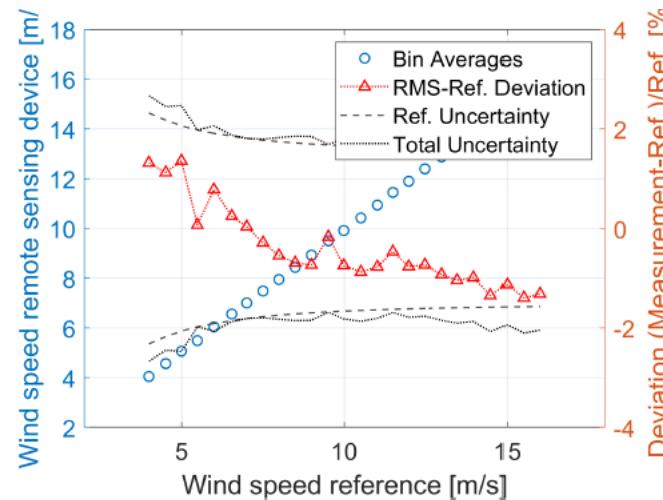
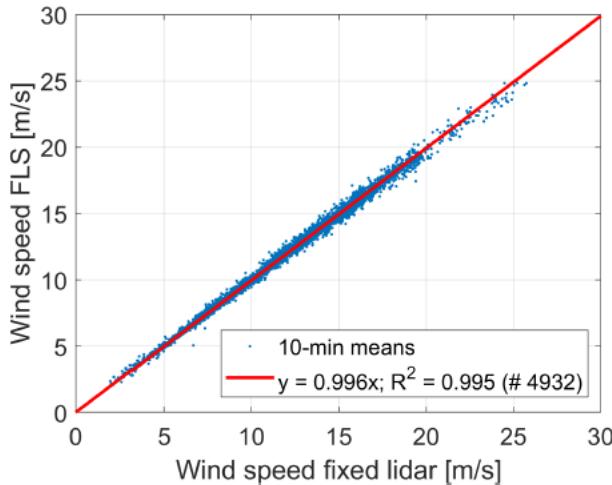
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- Motivation – Applications of dual-collocation
- Introduction of triple collocation
- Case studies / datasets
- Results for triple collocation
- Discussion and conclusions

# Motivation

## Application of dual collocations

Example 1: Performance verification (PV) / calibration of Floating Lidar System (FLS) at offshore met. mast



Gerrit Wolken-Möhlmann et al 2022 J. Phys.: Conf. Ser. 2362 012042, doi:10.1088/1742-6596/2362/1/012042

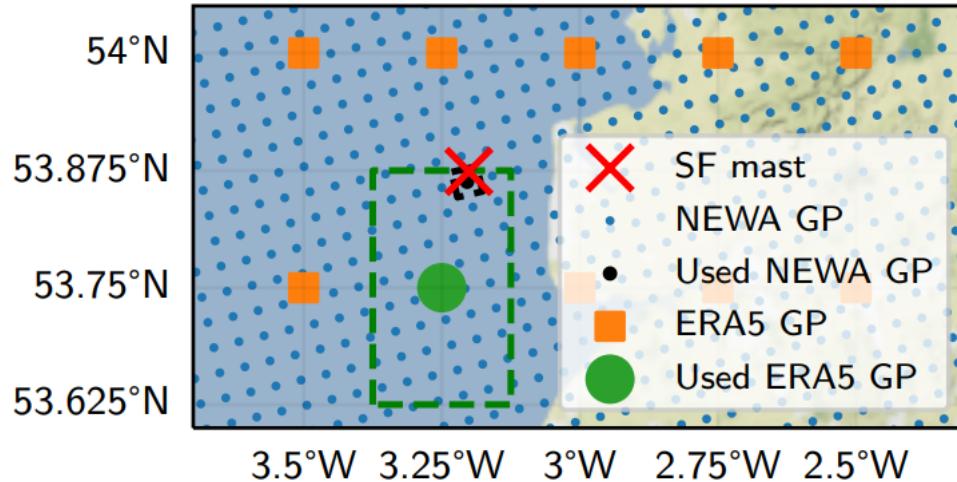
- Met. mast is used as reference here; but FLS data can also be compared to fixed lidar profiler (at mast platform) or reanalysis data (e.g., ERA 5)



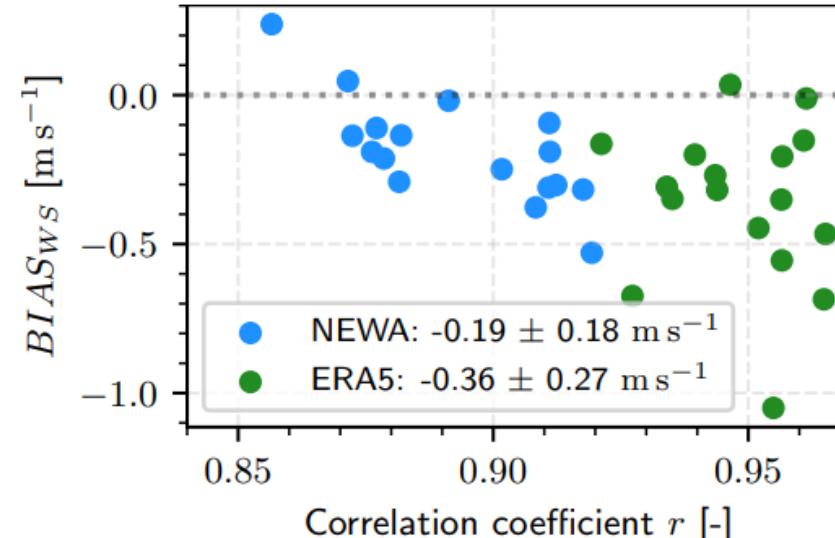
# Motivation

## Application of dual collocations

Example 2: Validating a mesoscale model (NEWA / WRF) and ERA5 for assessing offshore wind resources



P J Meyer and J Gottschall 2022 J. Phys.: Conf. Ser. 2151 012009,  
doi:10.1088/1742-6596/2151/1/012009



- (Downscaled) mesoscale model shows lower bias but also lower correlation to in-situ measurements .. what does qualify a numerical dataset as wind resource data source?

# Motivation

Application of dual collocation (→ conventional 2D linear regression analysis)

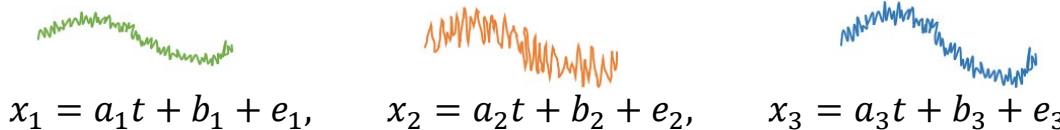
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- Implicit assumption in dual comparisons: all errors are due to the system that is being tested
- Reference system is assumed perfect (what if there are several possible references?)
- For PV / calibration, a reference uncertainty is defined but typically not considered in the regression analysis
- Is there a way to consider “scales” of data sources as well (?)

# Introduction of triple collocation

As an alternative method, proposed by Stoffelen [J. Geophys. Res. 103C3, 7755-7766 (1998), DOI:[10.1029/97JC03180](https://doi.org/10.1029/97JC03180)]

1. Start with three systems



2. Take one system ( $x_1$ ) to be the reference system

$$a_1 = 1, \quad b_1 = 0, \quad \rightarrow x_1 = t + e_1$$

3. Calculate the calibration coefficients for the other two systems

$$a_2 = \frac{C_{23}}{C_{13}}, \quad a_3 = \frac{C_{23}}{C_{12}}, \quad b_2 = M_2 - a_2 M_1, \quad b_3 = M_3 - a_3 M_1$$

4. Calculate the error variances

$$\sigma_1^2 = C_{11} - \frac{C_{13}C_{12}}{C_{23}}, \quad \sigma_2^2 = C_{22} - \frac{C_{21}C_{23}}{C_{13}}, \quad \sigma_3^2 = C_{33} - \frac{C_{13}C_{23}}{C_{12}}$$

TC output

\* $M$  and  $C$  denote the mean and covariance, respectively;  
Method is performed iteratively

Estimates for ..
$a_1, b_1$
$a_2, b_2$
$a_3, b_3$
$\sigma_{e1}^2$
$\sigma_{e2}^2$
$\sigma_{e3}^2$

w.r.t the  
reference  
system

changes

w.r.t the truth

# Introduction of triple collocation

As an alternative method, proposed by Stoffelen [J. Geophys. Res. 103C3, 7755-7766 (1998), DOI:[10.1029/97JC03180](https://doi.org/10.1029/97JC03180)]

1. Start with three systems


$$x_1 = a_1 t + b_1 + e_1, \quad x_2 = a_2 t + b_2 + e_2, \quad x_3 = a_3 t + b_3 + e_3$$

2. Take one system ( $x_1$ ) to be the reference system

$$a_1 = 1, \quad b_1 = 0, \quad \rightarrow x_1 = t + e_1$$

3. Calculate the calibration coefficients for the other two systems

$$a_2 = \frac{C_{23}}{C_{13}}, \quad a_3 = \frac{C_{23}}{C_{12}}, \quad b_2 = M_2 - a_2 M_1, \quad b_3 = M_3 - a_3 M_1$$

4. Calculate the error variances

$$\sigma_1^2 = C_{11} - \frac{C_{13}C_{12}}{C_{23}}, \quad \sigma_2^2 = C_{22} - \frac{C_{21}C_{23}}{C_{13}}, \quad \sigma_3^2 = C_{33} - \frac{C_{13}C_{23}}{C_{12}}$$

TC output

\* $M$  and  $C$  denote the mean and covariance, respectively;  
Method is performed iteratively as outlined in [1]

## Key assumptions

- Linear calibration is sufficient
- Reference system is calibrated and unbiased ( $a_1 = 1, b_1 = 0$ )
- Random error has a constant variance across the range of measurement values ( $\langle e_\alpha^2 \rangle = \sigma_{e_\alpha}^2, \alpha = 1, 2, 3$ )
- Random errors are uncorrelated ( $\langle e_\alpha e_\beta \rangle = 0, \alpha, \beta = 1, 2, 3$ )

## Estimates for ..

$a_1, b_1$
$a_2, b_2$
$a_3, b_3$
$\sigma_{e1}^2$
$\sigma_{e2}^2$
$\sigma_{e3}^2$

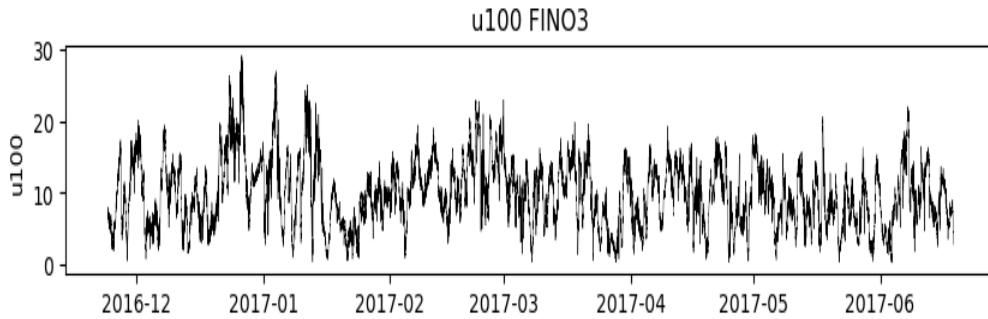
w.r.t the reference system

w.r.t the truth

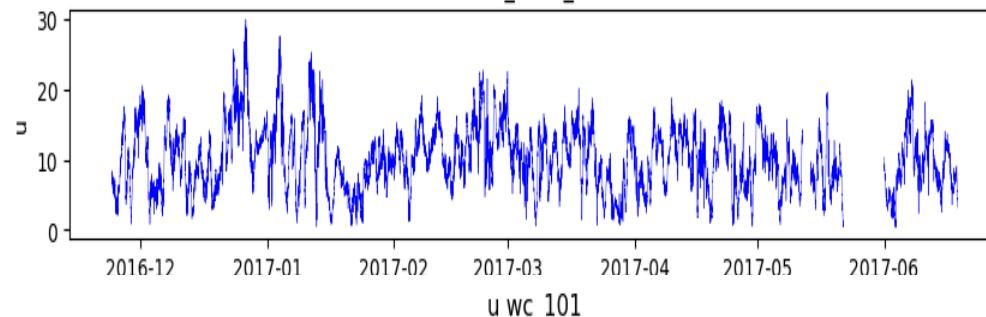
# Case study #1

## Description of datasets

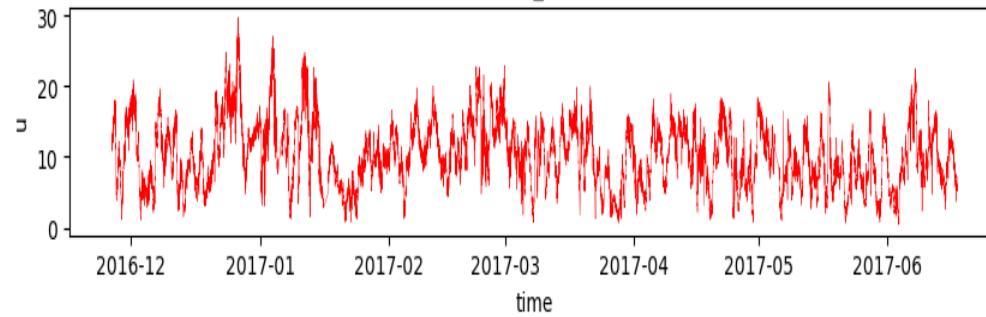
Met. mast



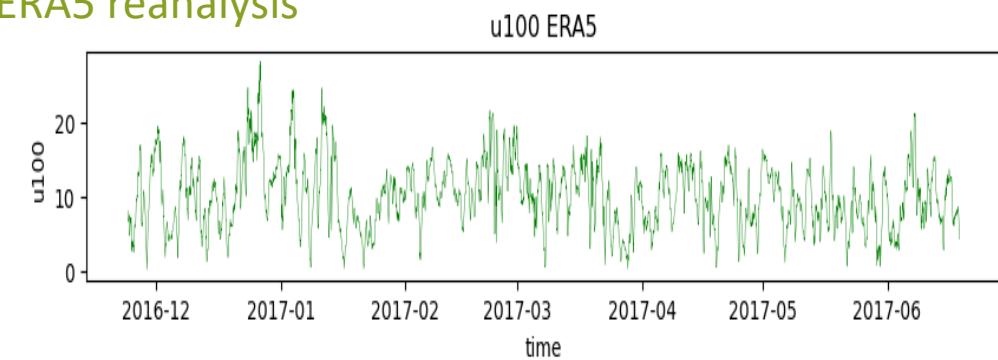
Fixed lidar



Floating lidar



ERA5 reanalysis



# Case study #1

## Results for triple collocation

### Model

Met. mast

Fixed lidar

Floating lidar

ERA5

#### 1 parameter

$$X = \beta_X T + e_X,$$

$$Y = \beta_Y T + e_Y,$$

$$Z = \beta_Z T + e_Z,$$

#### 2 parameters

$$x = X + e_x \equiv T + e_x$$

$$y = Y + e_y \equiv \alpha_1 + \beta_1 T + e_y$$

$$z = Z + e_z \equiv \alpha_2 + \beta_2 T + e_z$$

X

Y

Z

	1 param	2 param
$\alpha_Y$	N/A	0.153
$\alpha_Z$	N/A	0.301
$\beta_Y$	1.008	0.995
$\beta_Z$	1.015	0.991
$\sigma_{e_X}^2$	0.224	0.216
$\sigma_{e_Y}^2$	0.047	0.050
$\sigma_{e_Z}^2$	0.182	0.174

- Highest error variance found for met. mast (not FLS), lowest for fixed lidar

## Case study #1

### Results for triple collocation

X

	2 param
$\alpha_Y$	0.106
$\alpha_Z$	0.911
$\beta_Y$	1.000
$\beta_Z$	0.920
$\sigma_{e_X}^2$	0.136
$\sigma_{e_Y}^2$	0.090
$\sigma_{e_Z}^2$	1.430

Z

X

	2 param
$\alpha_Y$	0.259
$\alpha_Z$	1.052
$\beta_Y$	0.995
$\beta_Z$	0.915
$\sigma_{e_X}^2$	0.302
$\sigma_{e_Y}^2$	0.090
$\sigma_{e_Z}^2$	1.431

X

	2 param
$\alpha_Y$	0.106
$\alpha_Z$	0.911
$\beta_Y$	1.000
$\beta_Z$	0.920
$\sigma_{e_X}^2$	0.136
$\sigma_{e_Y}^2$	0.090
$\sigma_{e_Z}^2$	1.430

Y

Z

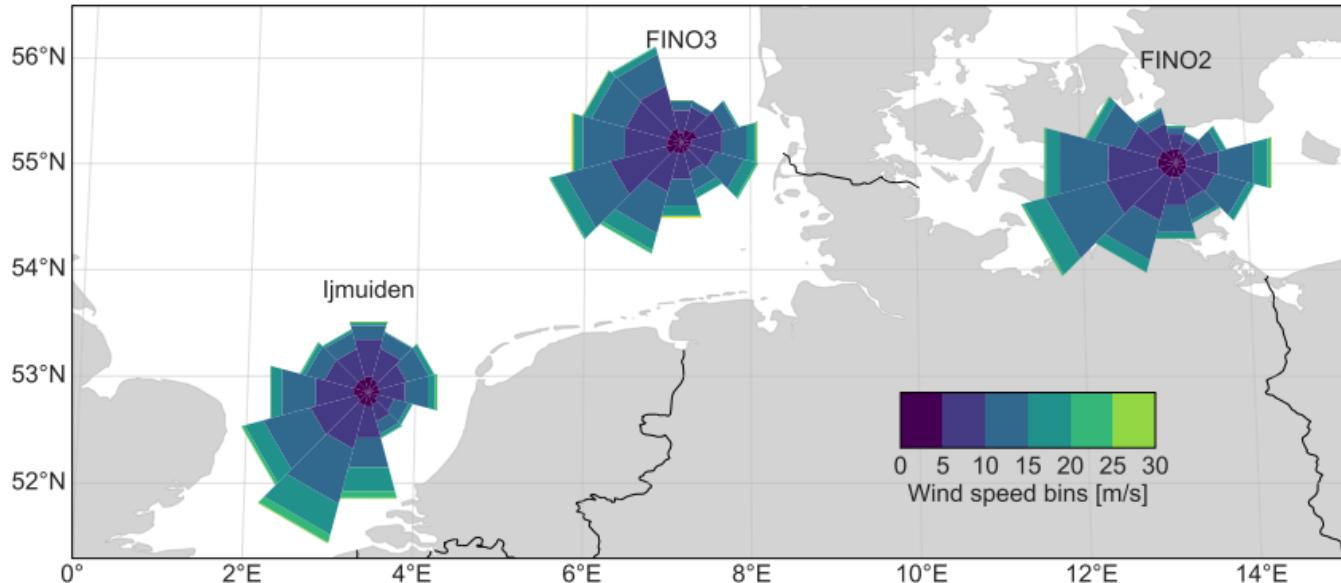
Met. mast  
Fixed lidar  
Floating lidar  
ERA5

- Error variance for reanalysis data always highest, for FLS always lowest

## Case study #2

### Description of datasets

- Wind speed date from (3) met. masts



Jonietz Alvarez et al., Wind Energ. Sci. Discuss. [preprint],  
<https://doi.org/10.5194/wes-2023-127>, in review, 2023.

#### Ijmuiden

X = met mast 92 m  
Y = WRF model 100 m  
Z = ERA5 model 100 m

#### FINO3

X = met mast 91 m  
Y = WRF model 100 m  
Z = ERA5 model 100 m

#### FINO2

X = met mast 92 m  
Y = WRF model 100 m  
Z = ERA5 model 100 m

## Case study #2

### Results for triple collocation

#### Ijmuiden

	1 param	2 parameter
$\alpha_Y$	N/A	-0.158
$\alpha_Z$	N/A	-0.170
$\beta_Y$	0.952	0.965
$\beta_Z$	0.953	0.967
$\sigma_{e_X}^2$	1.456	1.450
$\sigma_{e_Y}^2$	1.034	1.035
$\sigma_{e_Z}^2$	0.436	0.436

#### Model:

##### 1 parameter

$$X = \beta_X T + e_X,$$

$$X = \beta_Y T + e_Y,$$

$$Z = \beta_Z T + e_Z,$$

##### 2 parameters

$$x = X + e_x \equiv T + e_x$$

$$y = Y + e_y \equiv \alpha_1 + \beta_1 T + e_y$$

$$z = Z + e_z \equiv \alpha_2 + \beta_2 T + e_z,$$

X = met mast 92 m

Y = WRF model 100 m

Z = ERA5 model 100 m

- Error variance for ERA5 lowest, for met. mast highest

## Case study #2

### Results for triple collocation

X = met mast  
Y = WRF model  
Z = ERA5 model

## Ijmuiden

	2 parameter
$\alpha_Y$	-0.158
$\alpha_Z$	-0.170
$\beta_Y$	0.965
$\beta_Z$	0.967
$\sigma_{e_X}^2$	1.450
$\sigma_{e_Y}^2$	1.035
$\sigma_{e_Z}^2$	0.436

## FINO3

	2 parameter
$\alpha_Y$	-0.411
$\alpha_Z$	-0.366
$\beta_Y$	1.061
$\beta_Z$	1.069
$\sigma_{e_X}^2$	1.597
$\sigma_{e_Y}^2$	1.047
$\sigma_{e_Z}^2$	0.386

## FINO2

	2 parameter
$\alpha_Y$	-0.282
$\alpha_Z$	-0.024
$\beta_Y$	0.965
$\beta_Z$	0.953
$\sigma_{e_X}^2$	1.675
$\sigma_{e_Y}^2$	0.944
$\sigma_{e_Z}^2$	0.561

# Discussion

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- Can typical wind [energy] data applications (cf. examples) benefit from triple collocation?
- May obtained error variances be related to uncertainty estimates?  $\leftrightarrow$  Traceable uncertainty quantification requires well defined reference uncertainty.
- Possible (already tested) applications: Measure-Correlate-Predict (MCP) for long-term extrapolation and/or short-term data gap filling
- Quadrupole collocation as possible (but considerably more complex) extension

# Summary

## Conclusions of this study

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- “Dual collocation” as a standard instrument for wind [energy] data analysis .. with inherent flaws
- Triple collocation may allow for a more “objective” evaluation → possibly helping to identify which datasets are most suited to represent the relevant offshore wind resource
- Most promising applications for
  - .. combining different types of data and future resource assessment methods
  - .. as well as measurement calibration standards



Thank you  
for your time!  
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