

Nikola Vasiljevic 

e-WindLidar toolbox

(online) NREL talk
30th Jun 2020

Usage license:

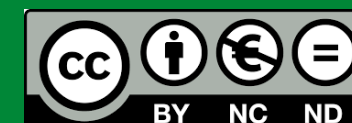


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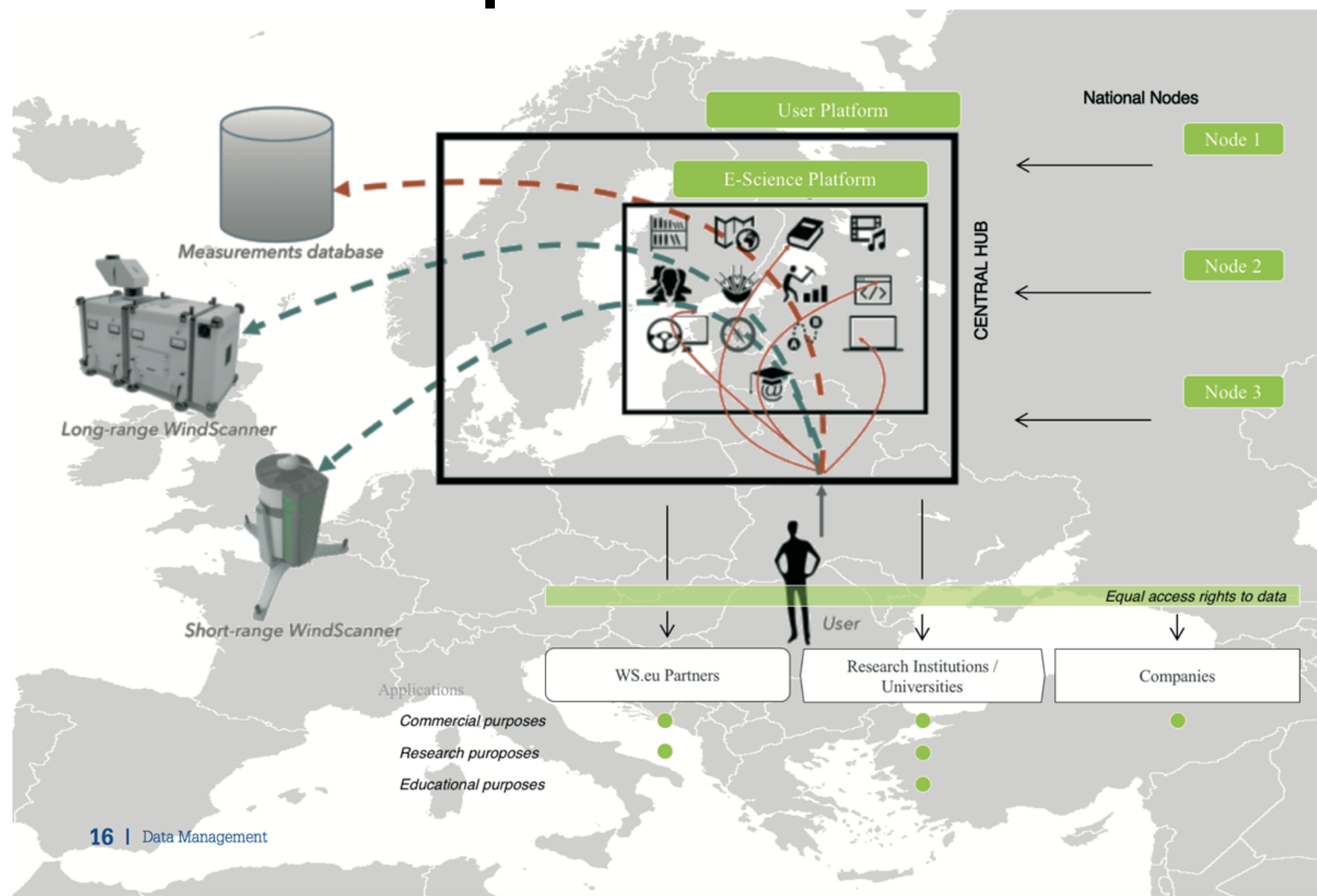
- e-WindLidar initiative
- *campaign-planning-tool*
- *YADDUM (Yet **A**nother **D**ual-**D**oppler **U**ncertainty **M**odel)*
- *mocalum (**M**onte-**C**arlo **L**idar **U**ncertainty **M**odel)*

e-WindLidar initiative

- Develop community-based tools that will simplify:
 - Planning and configuration of lidar-based field campaigns
 - Operation of lidars in field campaigns
 - Usage of lidar data
- e-WindLidar idea was conceived during the WindScanner.EU project under the name WindScanner Information System [1]

[1] <https://zenodo.org/record/1175211>

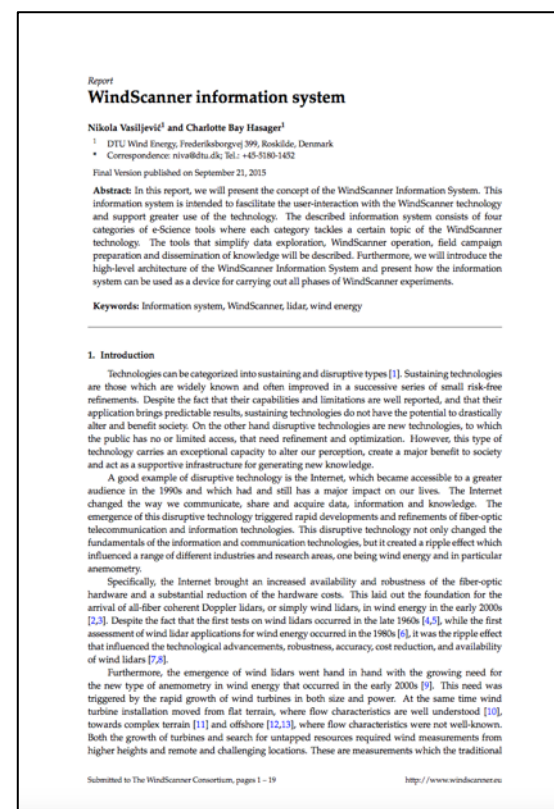
e-Science and user platform



Description

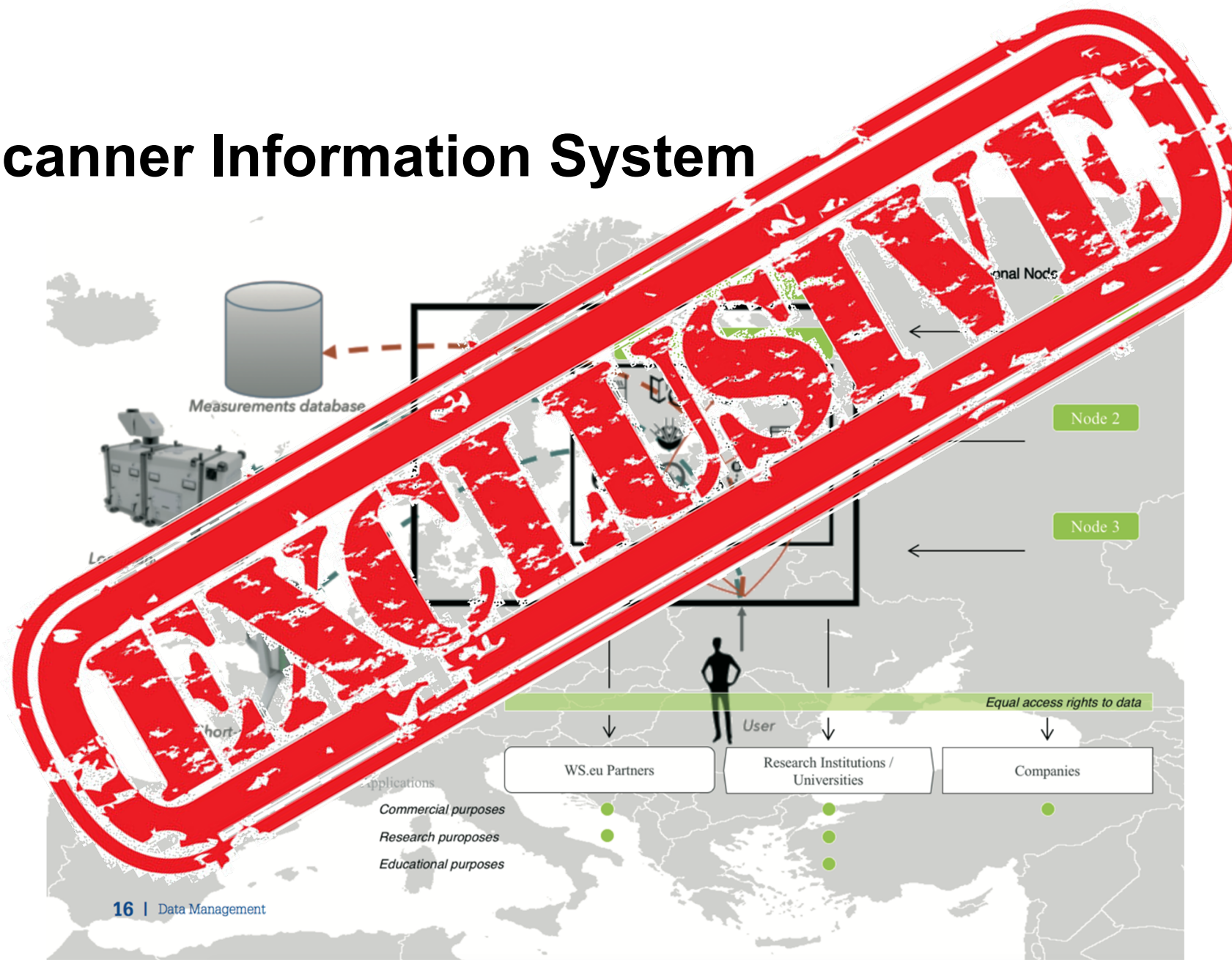


[Link](#)

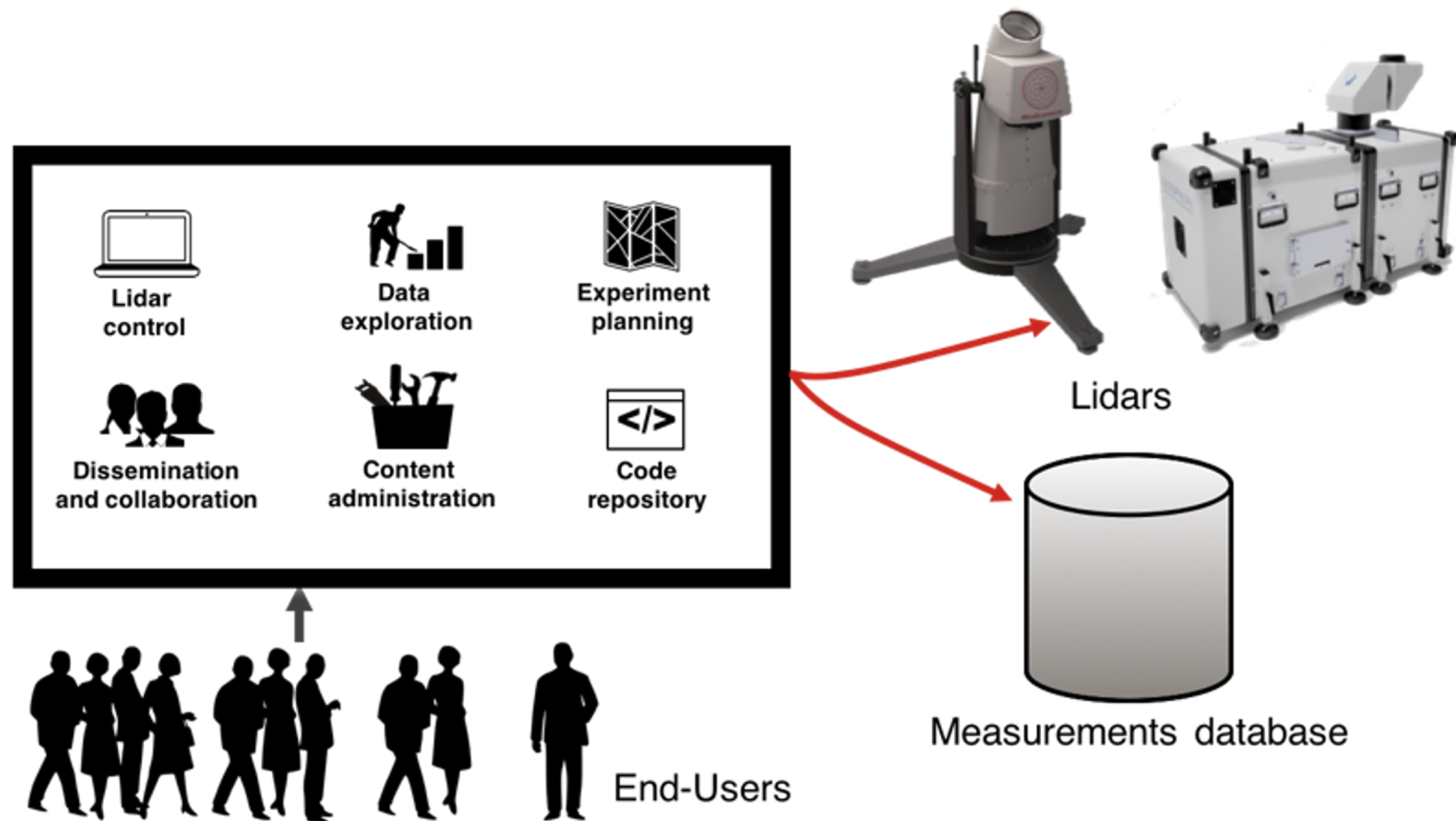


[Link](#)

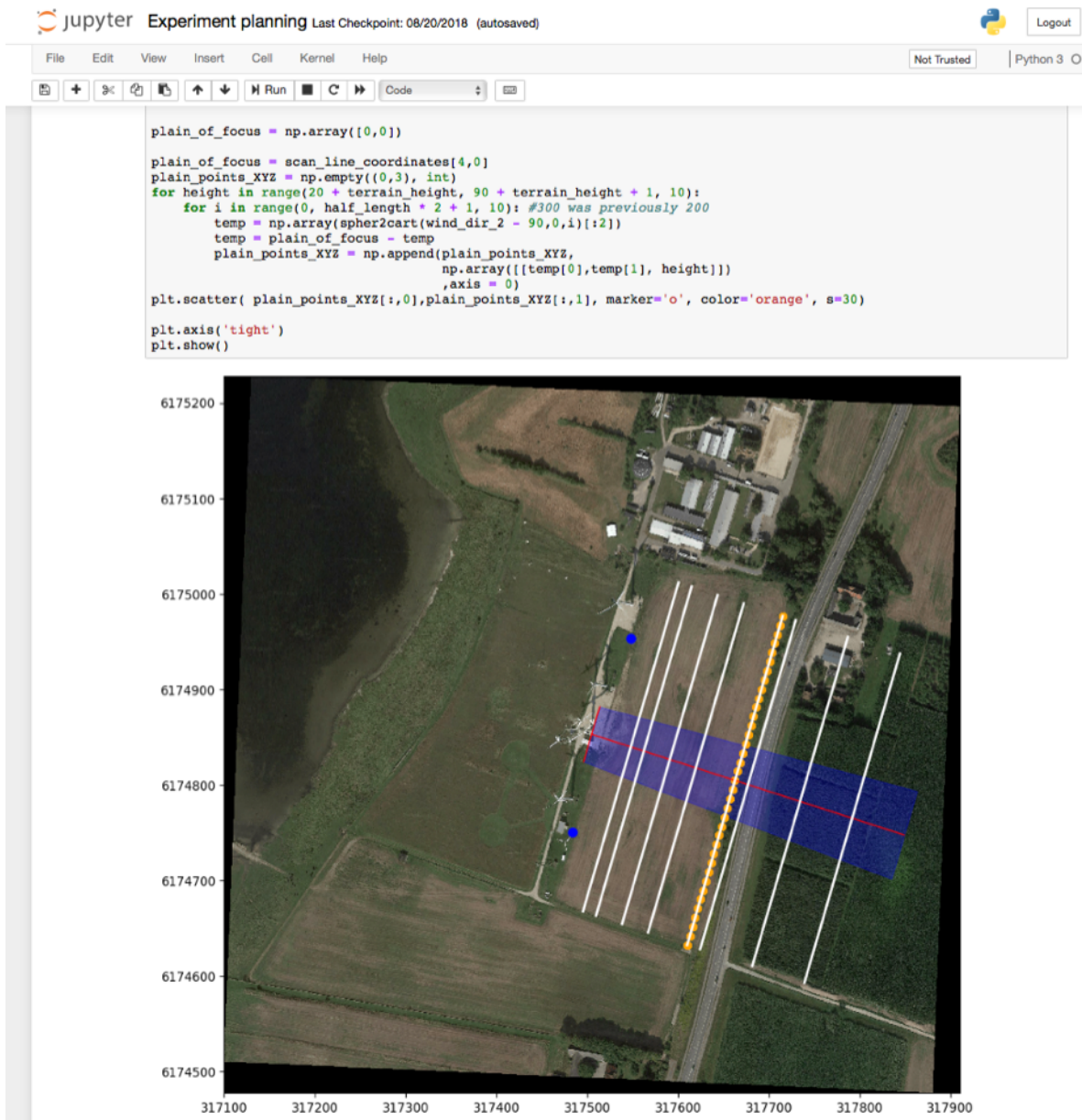
WindScanner Information System

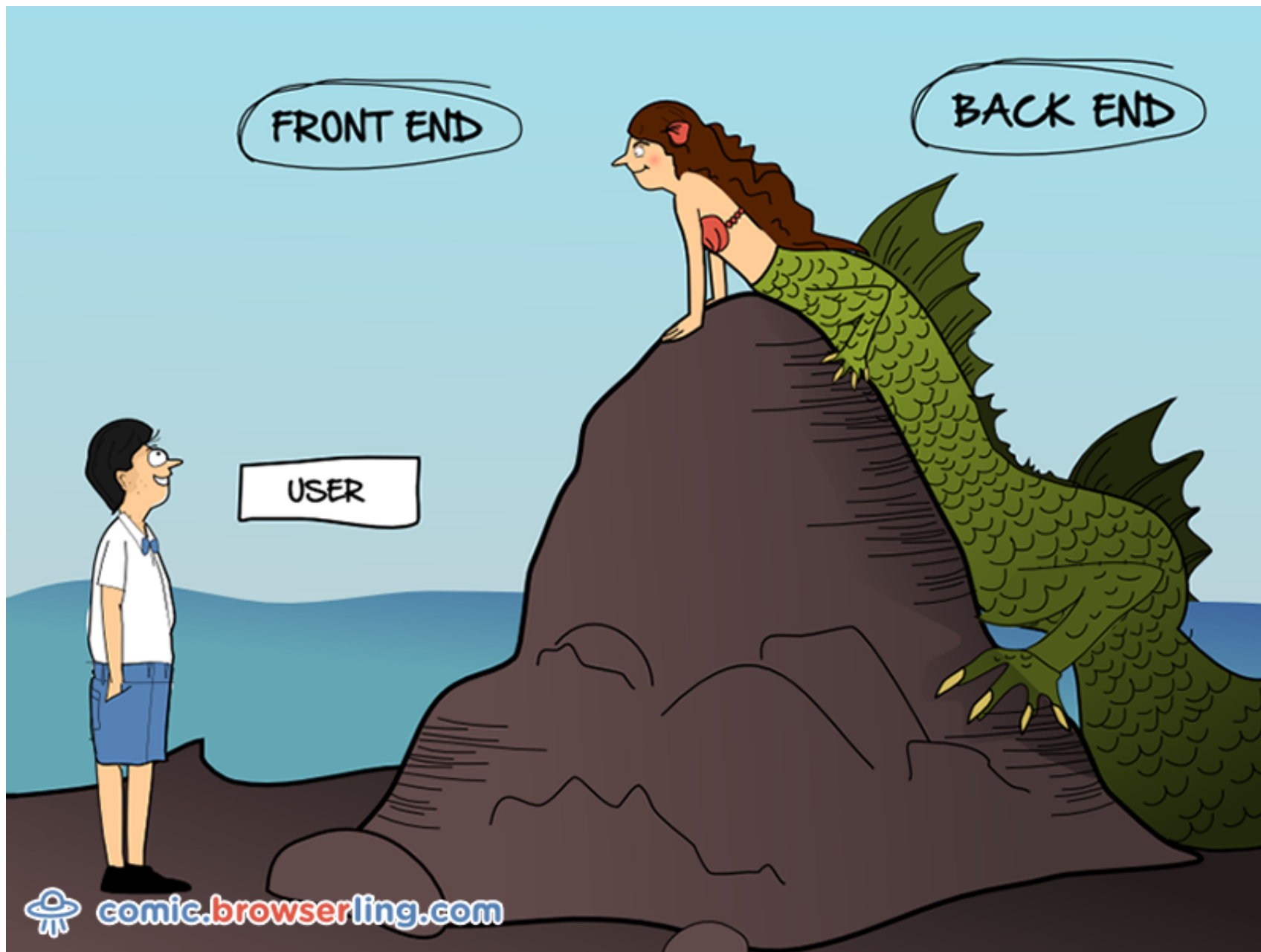


e-WindLidar toolbox



How a tool should look like?





campaign-planning-tool

Following slides are taken (and modified) from presentation :

*Vasiljevic, Nikola, Vignaroli, Andrea, Bechmann, Andreas, & Wagner, Rozenn. (2019, June). **Where to place WindScanners and where to measure with them?**. Zenodo. <http://doi.org/10.5281/zenodo.3247797>*

Full paper available:

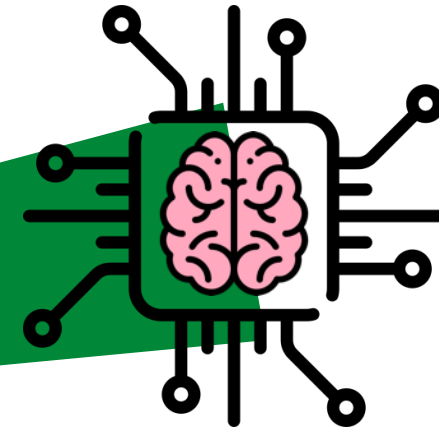
Nikola Vasiljević, Andrea Vignaroli, Andreas Bechmann, and Rozenn Wagner. (2020 January). **Digitalization of scanning lidar measurement campaign planning**. WES. <https://doi.org/10.5194/wes-5-73-2020>

campaign-planning-tool background

- Establish the campaign planning workflow
- **Digitalize** the workflow, thus create a tool
- Make the tool modular
- Base the tool on open source solutions
- Describe the tool
- Make the tool publicly available



Physical lidar expert



Digital lidar expert

Workflow Phases

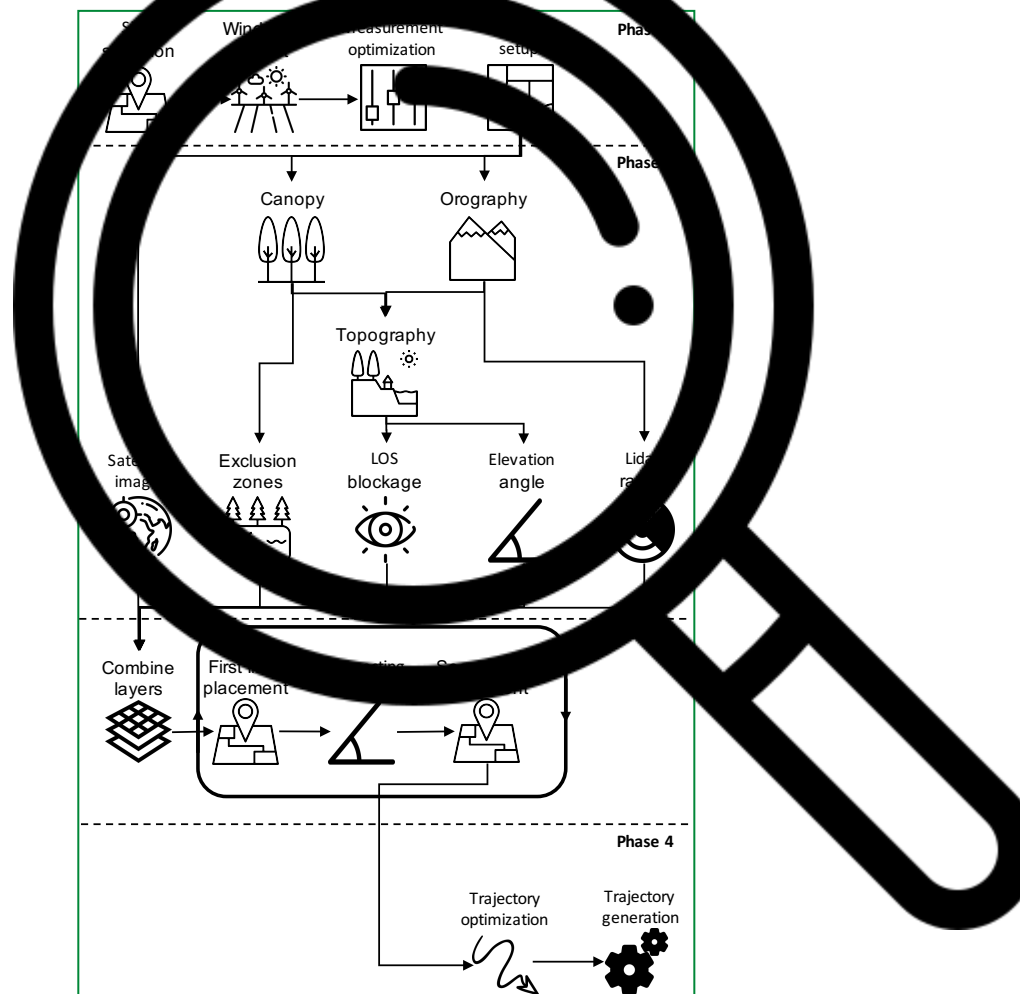
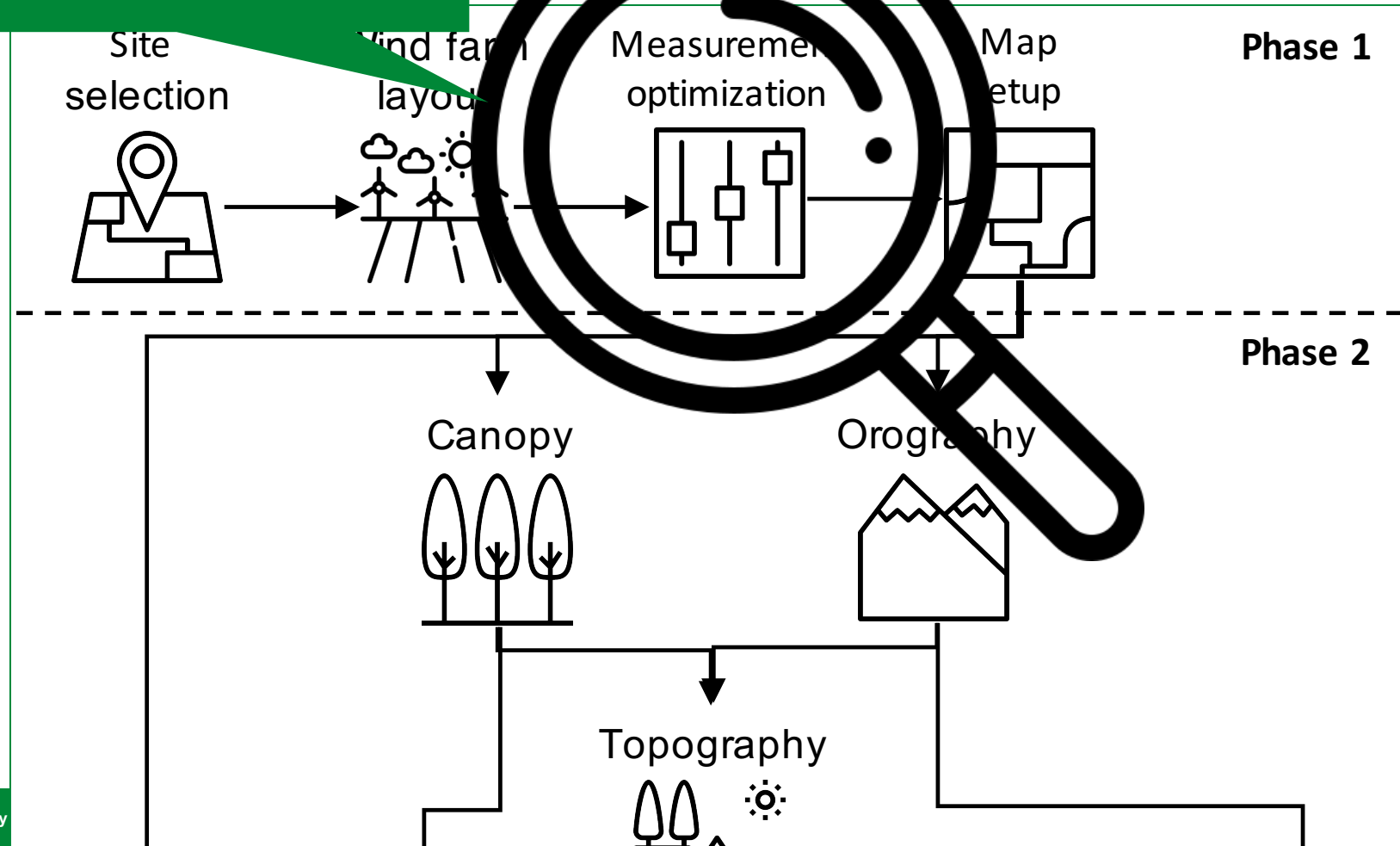
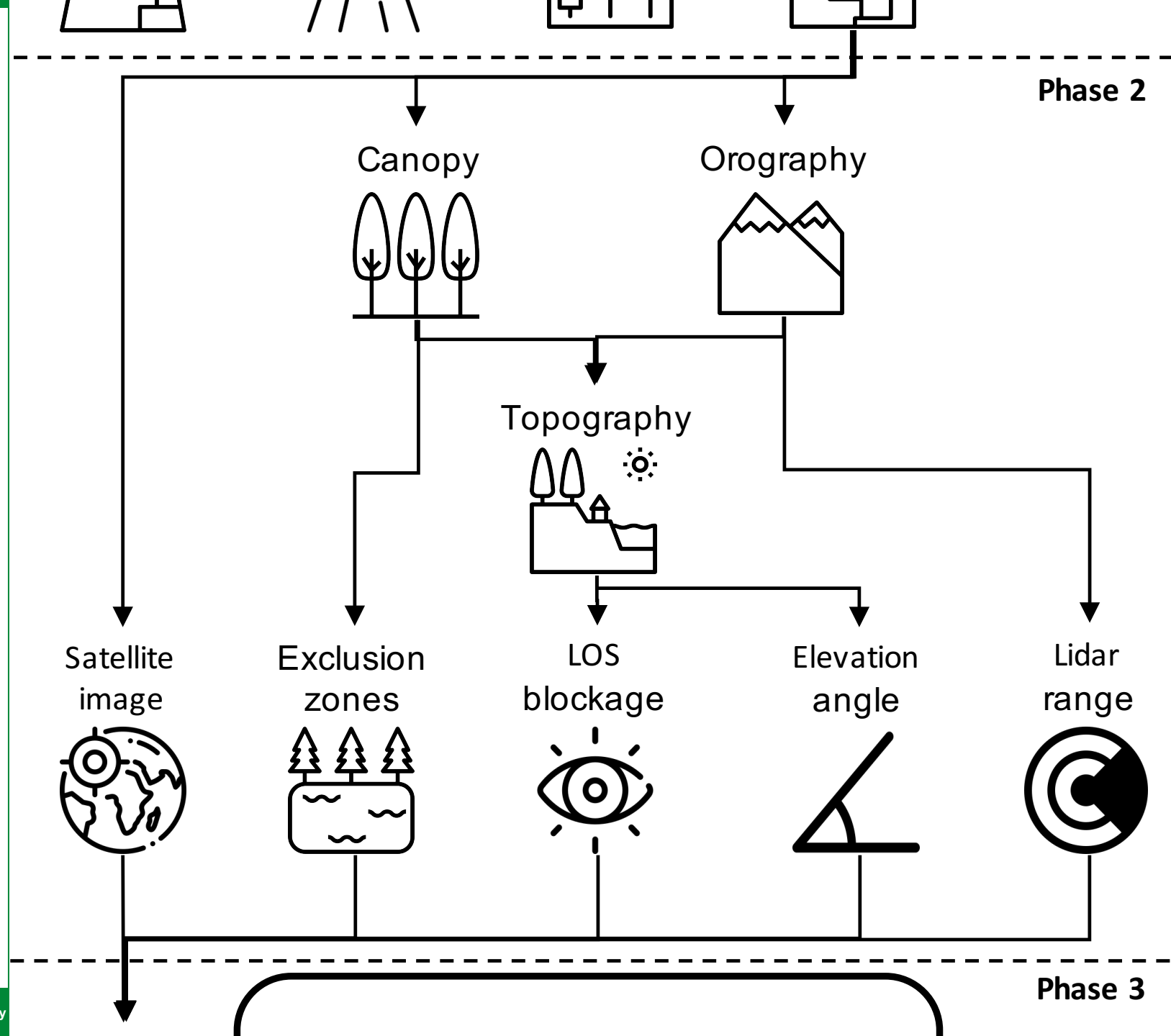


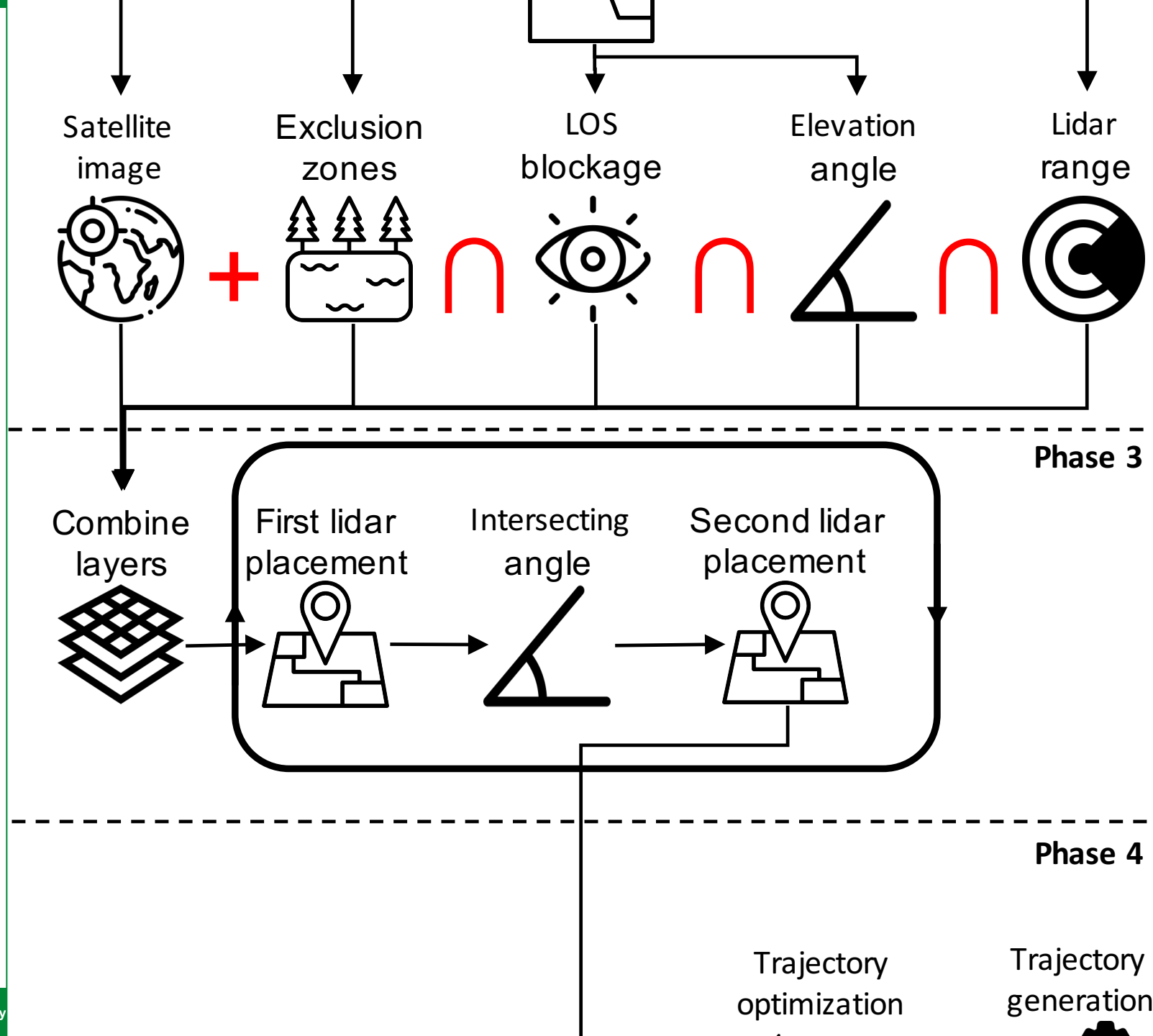
Image source: flaticon.com

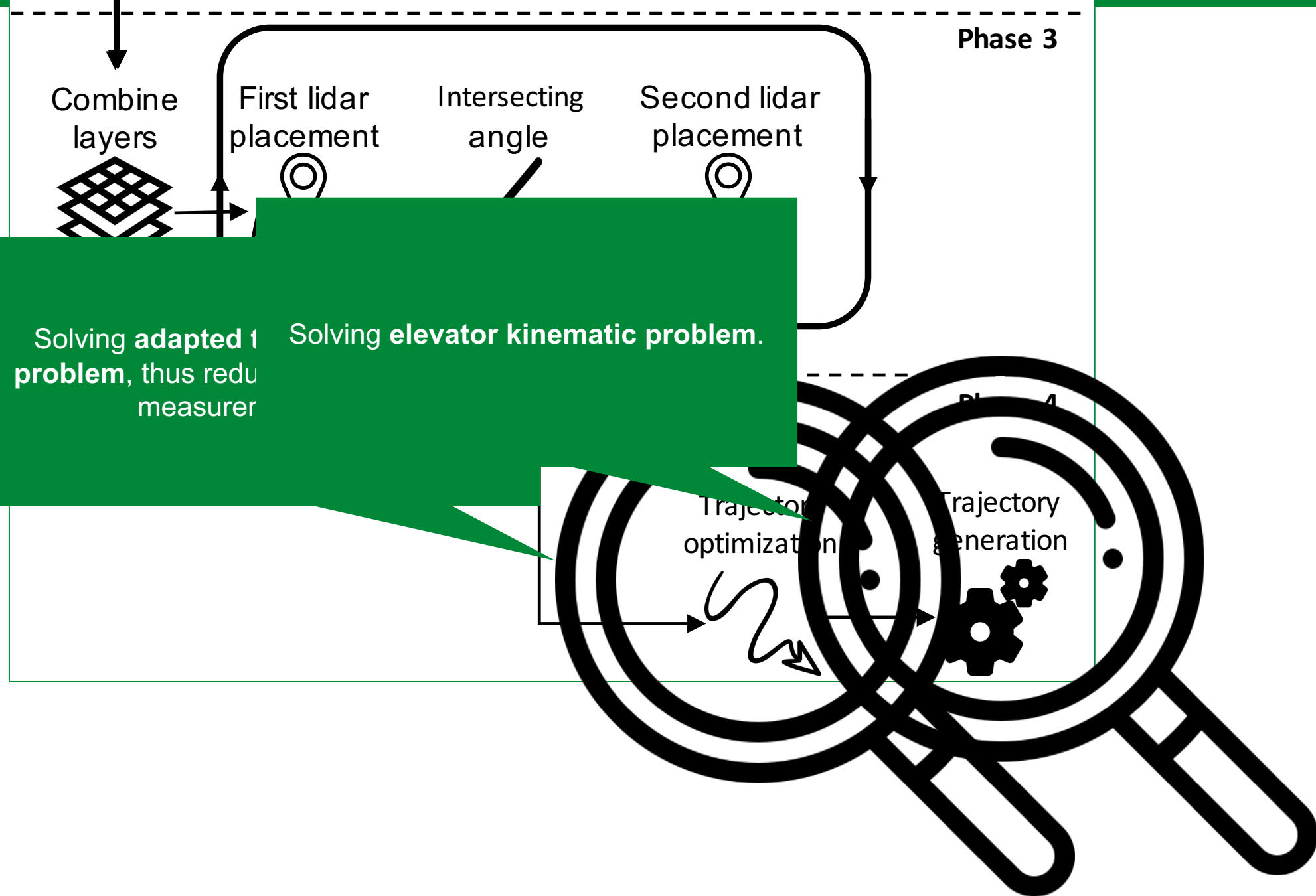
Solving **disc covering problem** in which we are searching for a minimum number of disks with a certain radius to cover all turbine positions.

Workflow Phases

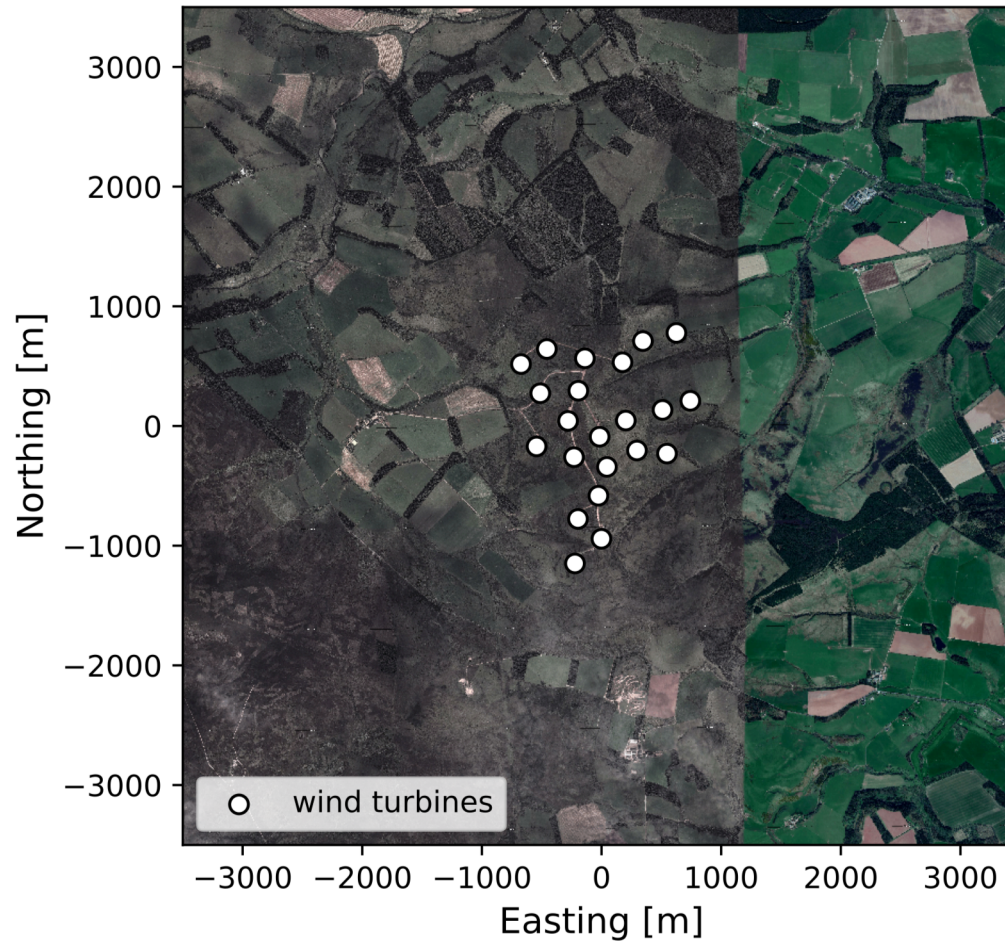








Example 1: Scottish site [2]

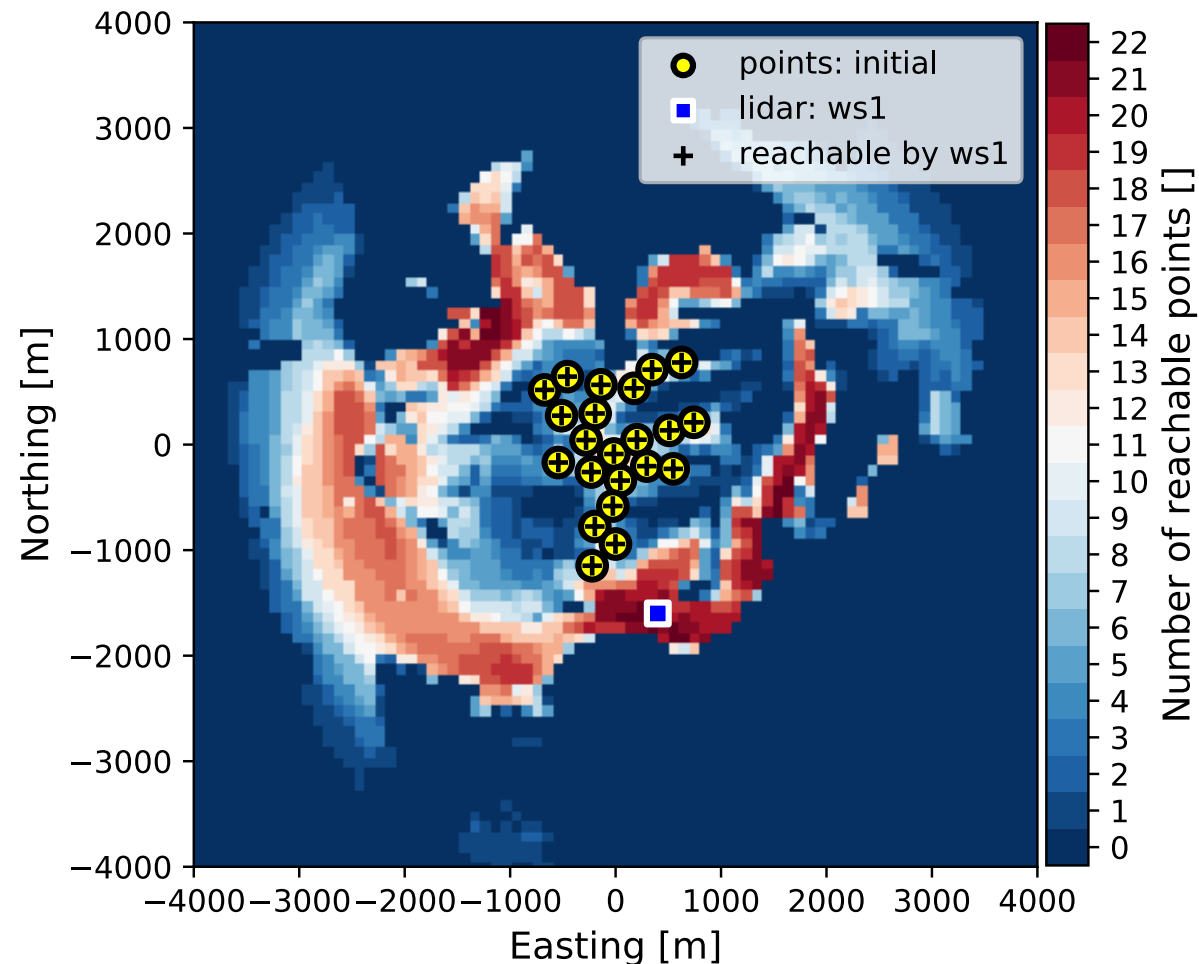


Info:

- 22 wind turbines with 47-m hub-heights
- Hilly terrain
- Aim to measure at each turbine position

[2] <https://doi.org/10.11583/DTU.8343989.v3>

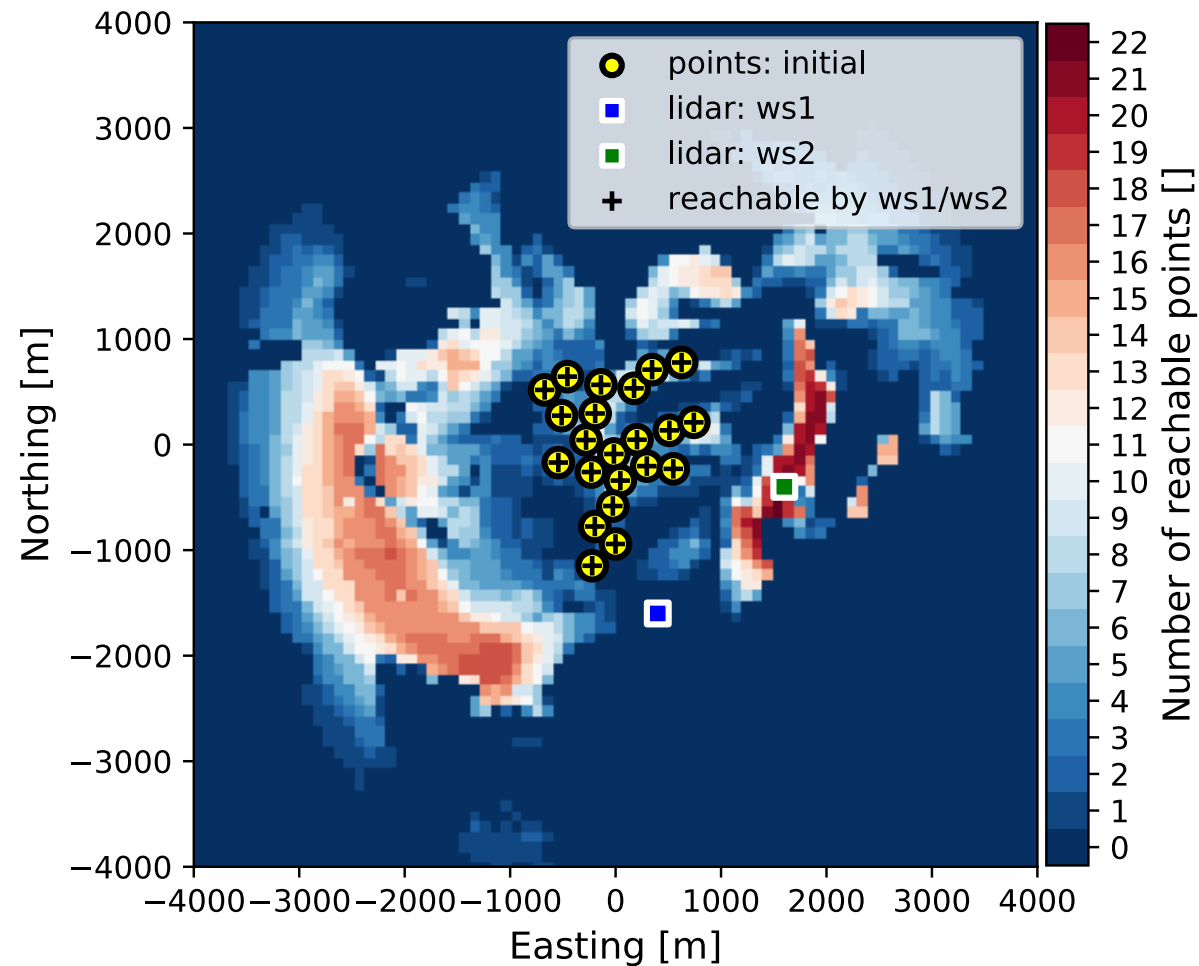
Example 1: Lidar placement GIS maps



Parameter	Value
Average range	3000 m
Max elevation angle	5°
Min intersecting angle	30°

Maps export to GeoTIFF / KML

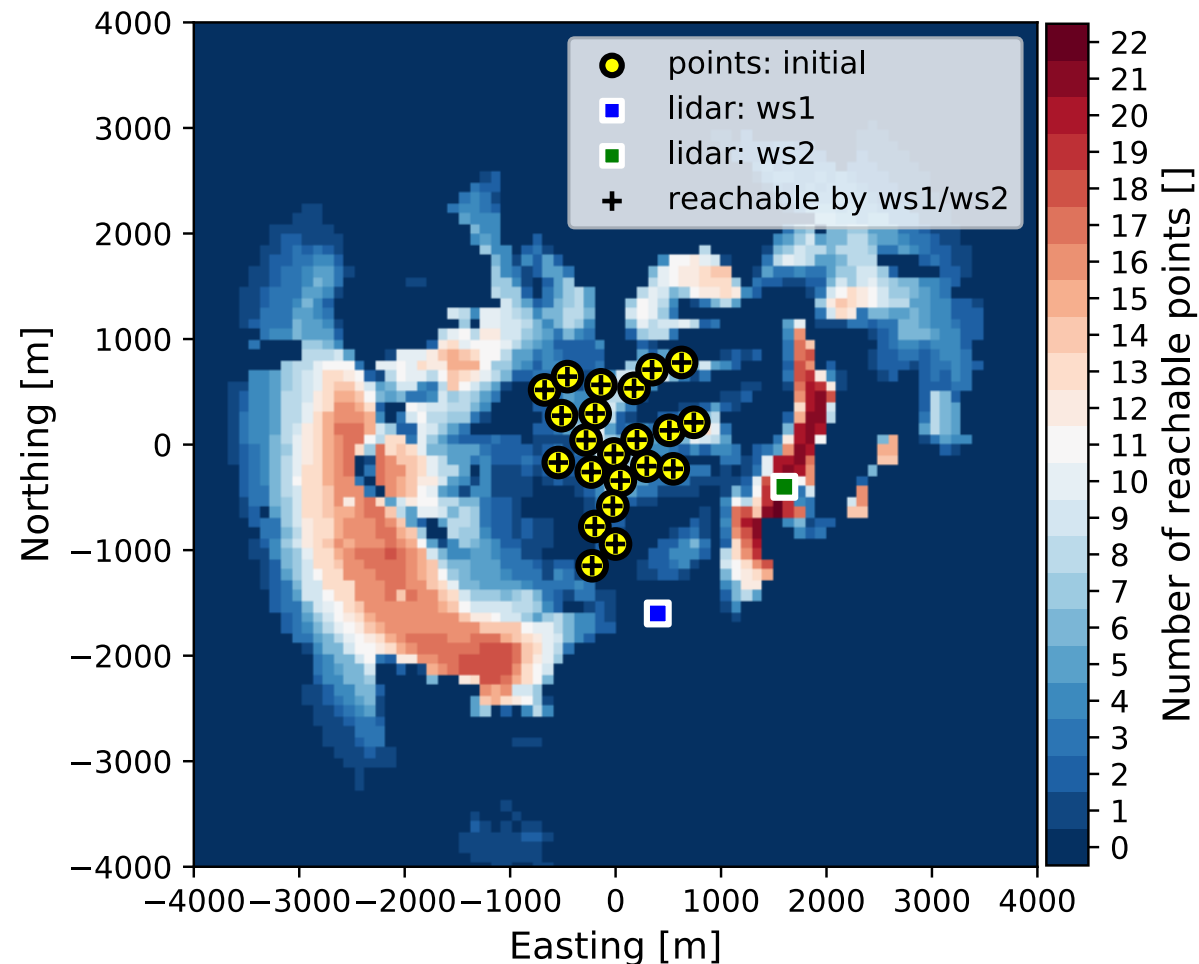
Example 1: Lidar placement GIS maps



Parameter	Value
Average range	3000 m
Max elevation angle	5°
Min intersecting angle	30°

Maps export to GeoTIFF / KML

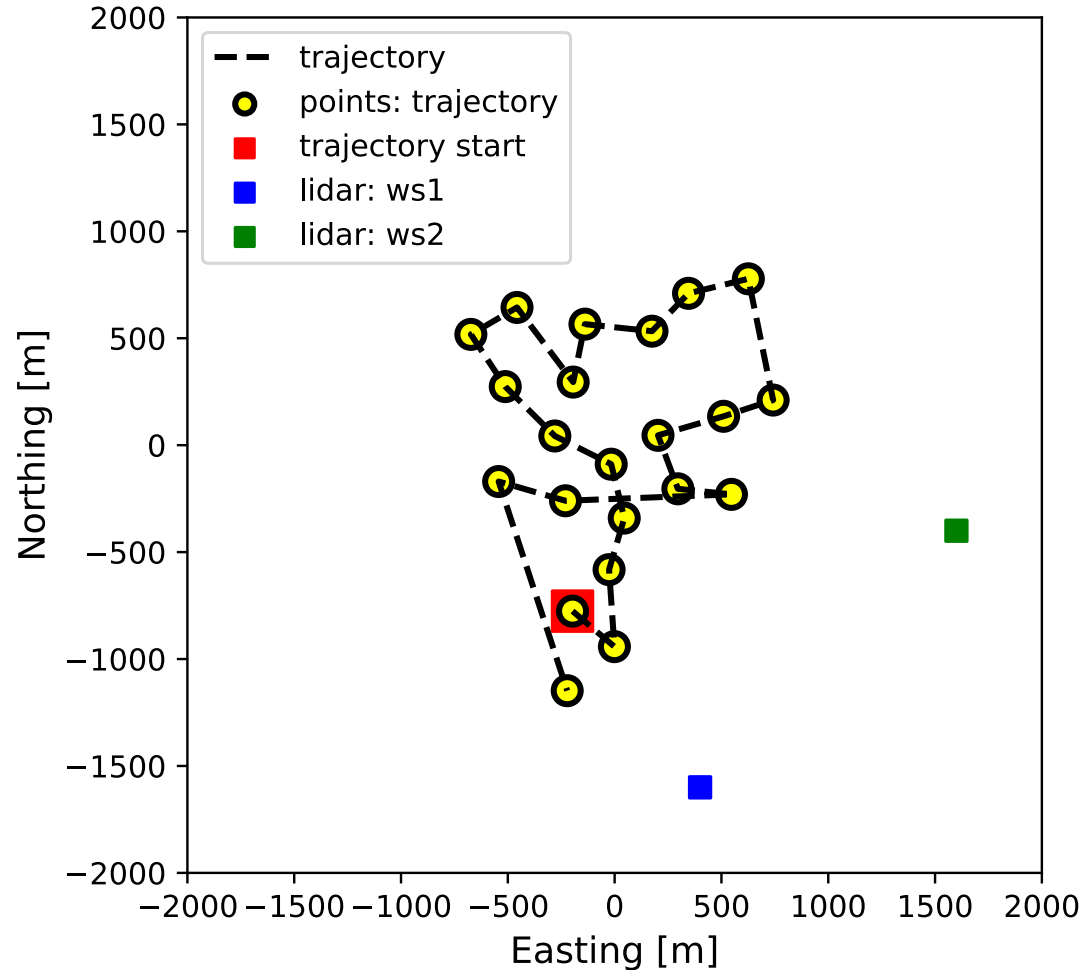
Example 1: Lidar placement GIS maps



Parameter	Value
Average range	3000 m
Max elevation angle	5°
Min intersecting angle	30°

Maps export to GeoTIFF / KML

Example 1: Trajectory optimization and generation



Parameter	Value
Max speed	50°/s
Max acceleration	100°/s ²
Measurement time	22 s
Motion time	14 s
Trajectory time	36 s



YAML



XML

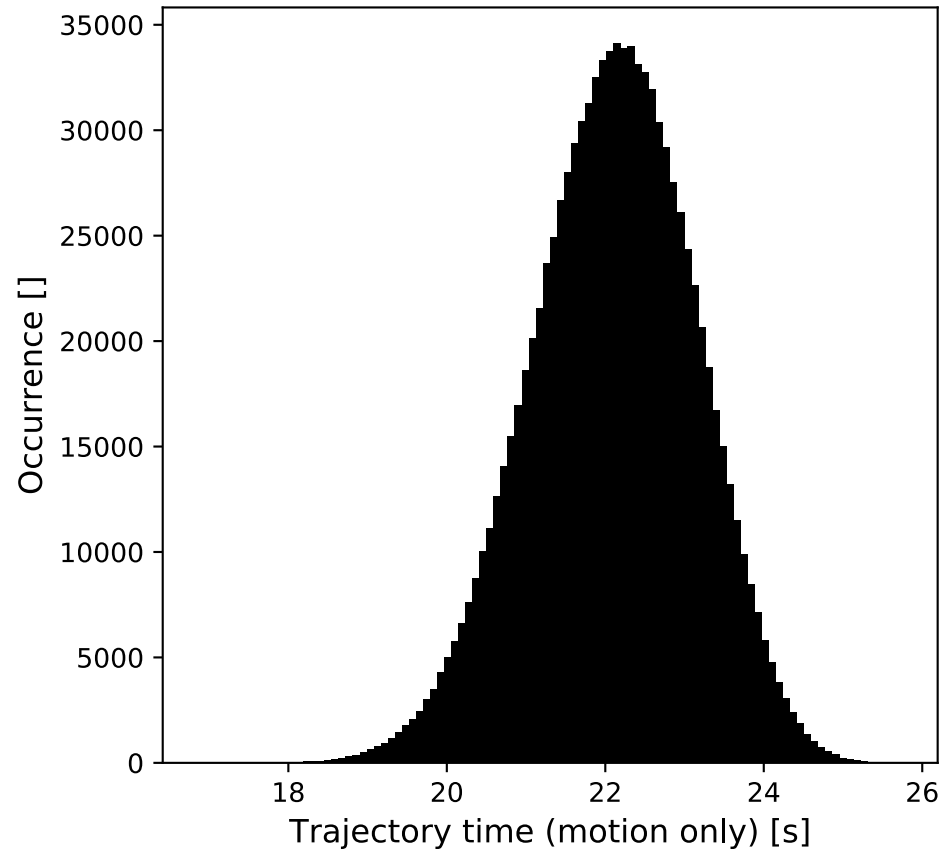
...



PMC

Results export in multiple files

Example 1: How well the trajectory is optimized?

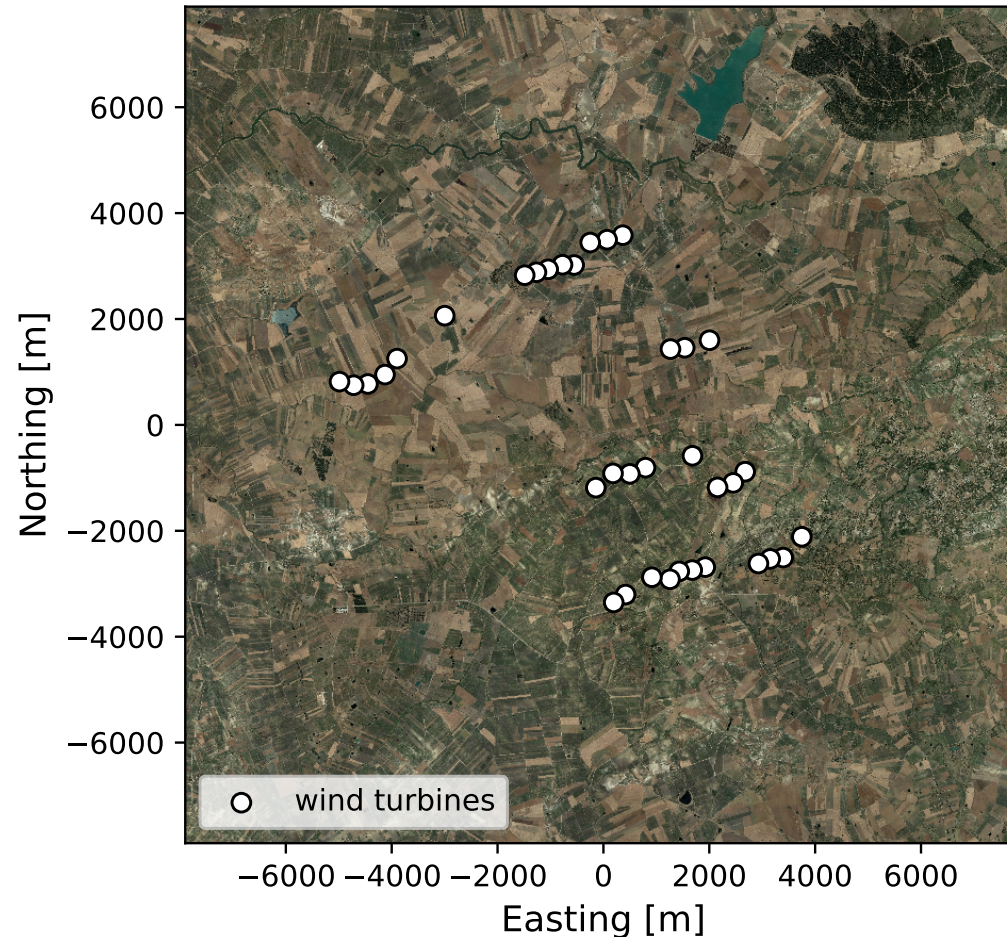


Parameter	Value
Mean motion time	22.09 s
Max motion time	25.76 s
Min motion time	17.15 s
Std motion time	1.03 s

A histogram of motion time for **10⁶** randomly generated trajectory configurations for the Scottish site.

On average the optimized trajectory is 8 s shorter in duration!

Example 2: Italian site [3]

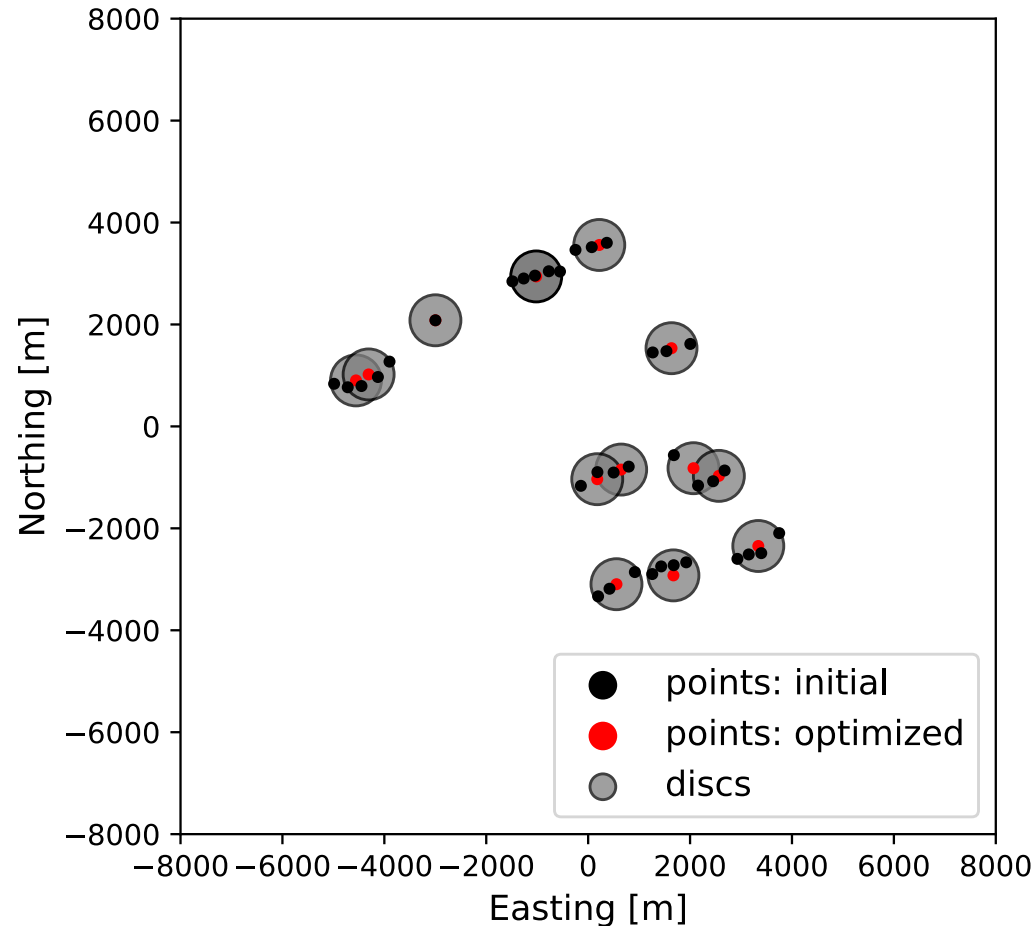


Info:

- 36 wind turbines with 78-m hub-heights
- Hilly terrain
- We will use measurement point optimization

[3] <https://doi.org/10.11583/DTU.8343989.v3>

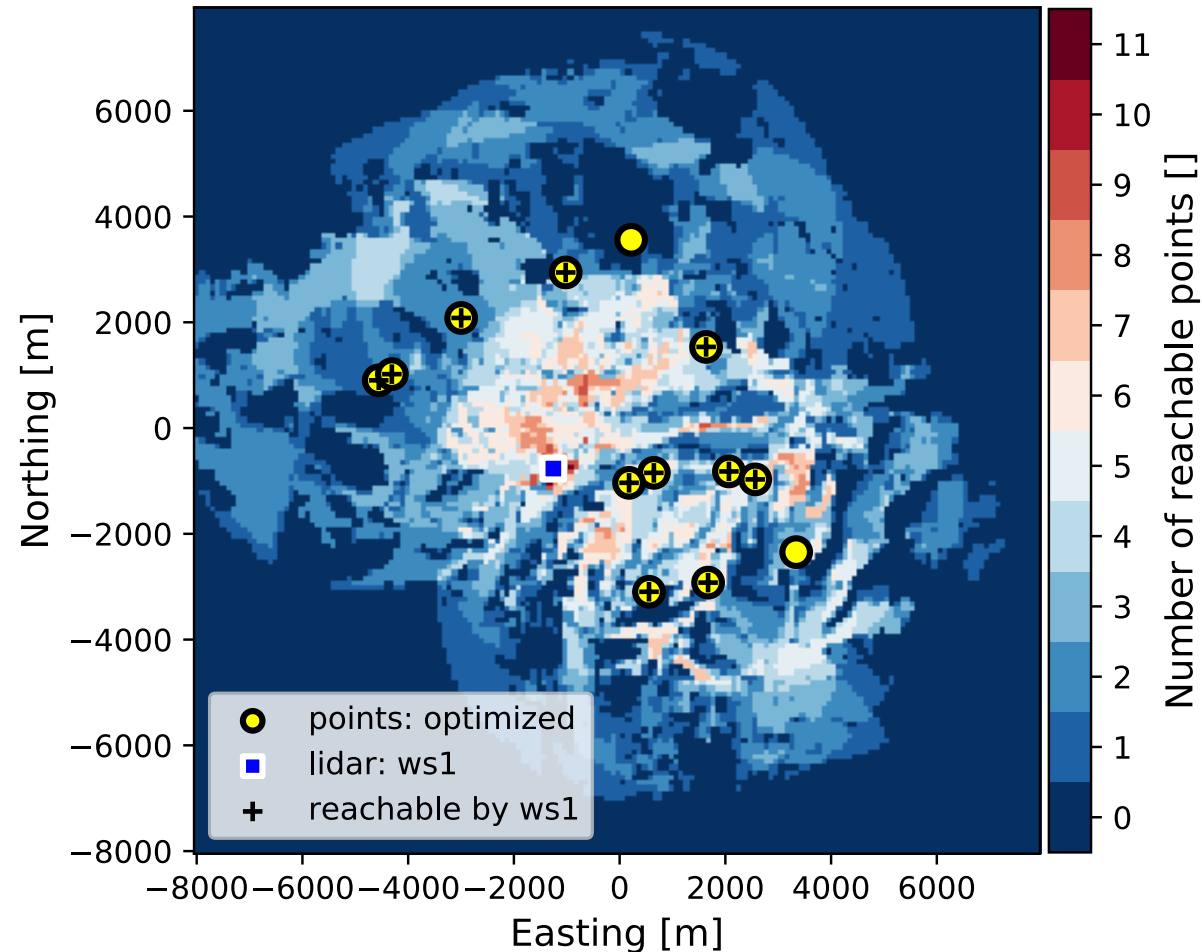
Example 2: Measurement point optimization



Parameter	Value
Representativeness radius [12]	500 m
No initial points	36
No optimized points	13

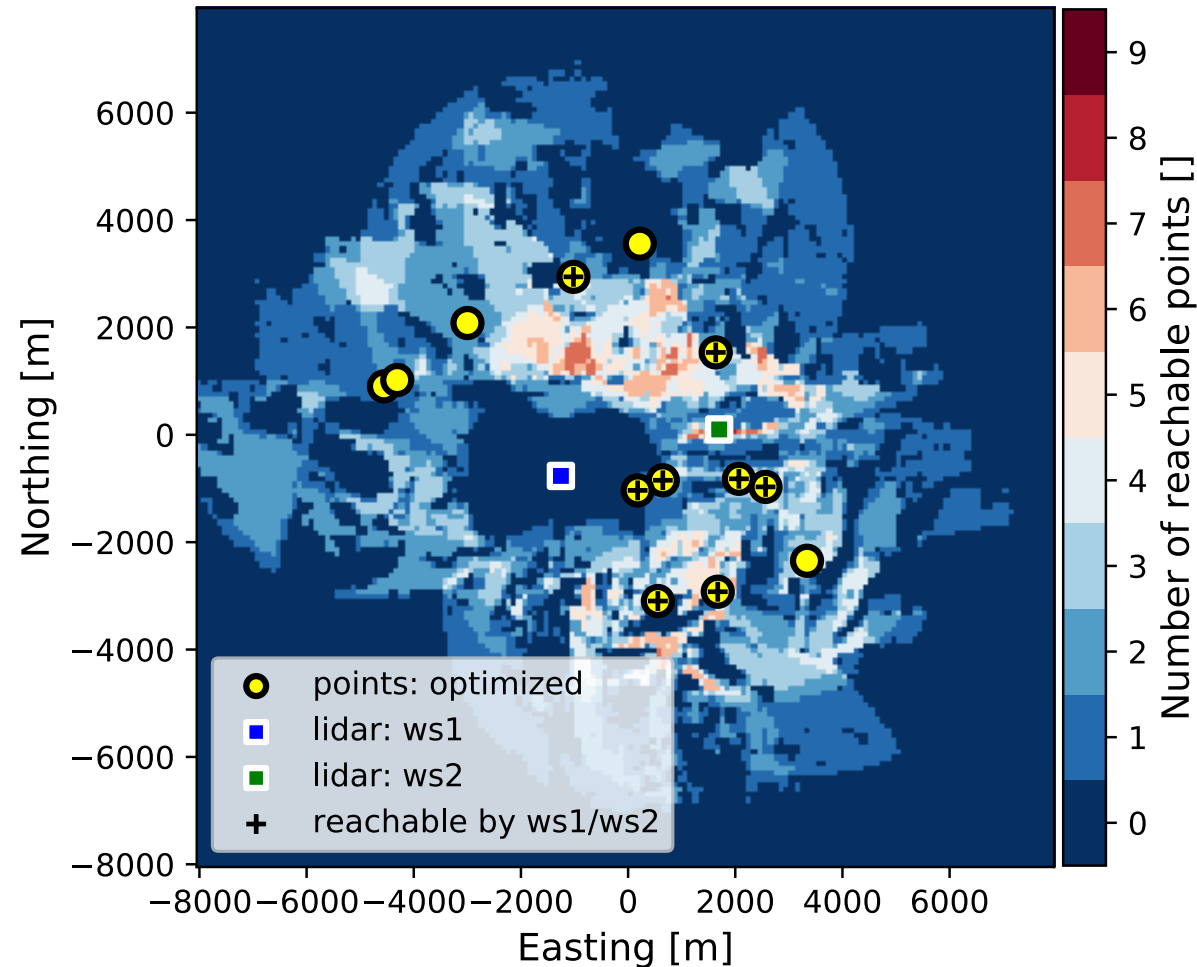
Reduction by 64%

Example 2: Lidar placement GIS maps



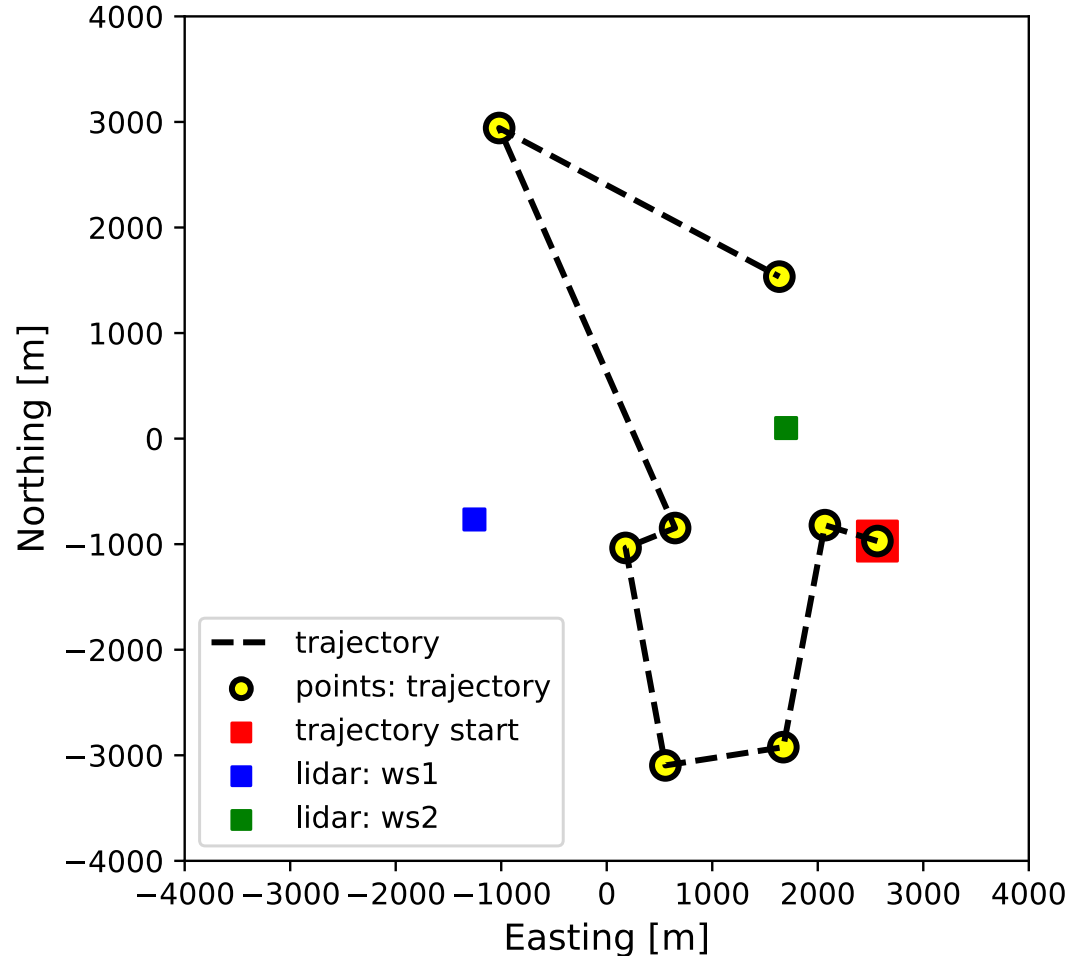
Parameter	Value
Average range	4000 m
Max elevation angle	5°
Min intersecting angle	30°

Example 2: Lidar placement GIS maps



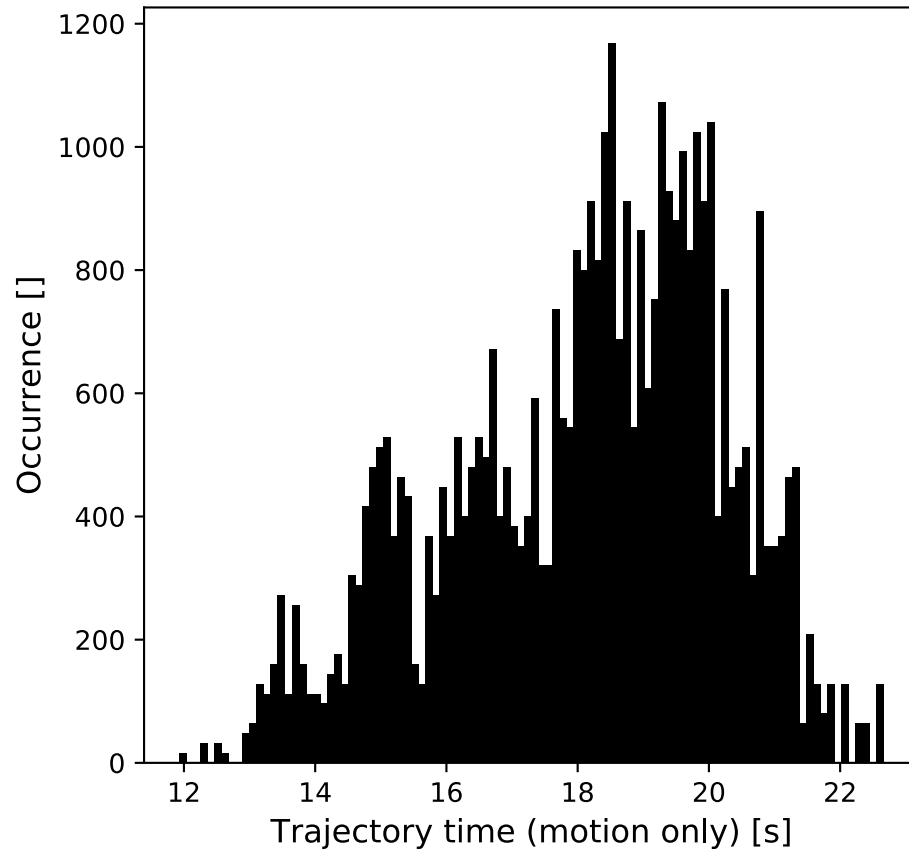
Parameter	Value
Average range	4000 m
Max elevation angle	5°
Min intersecting angle	30°

Example 2: Trajectory optimization and generation



Parameter	Value
Max speed	50°/s
Max acceleration	100°/s ²
Measurement time	8 s
Motion time	13 s
Trajectory time	21 s

Example 1: How well the trajectory is optimized?



Parameter	Value
Mean motion time	18.14 s
Max motion time	22.66 s
Min motion time	11.93 s
Std motion time	2.10 s

A histogram of motion time for 40320 unique trajectory configurations for the Italian site.

On average the optimized trajectory is 5 s shorter in duration!

Summary

- It takes **couple of minutes** to design and configure scanning lidar campaigns using *campaign-planning-tool* even for non-lidar experts, opposite to probably **days** if this is done manually by lidar experts
- The actual computational time to run *campaign-planning-tool* takes about **30 s**
- Optimizing measurement points can (depending on layout) reduce significantly number of measurement points => boost measurement rate
- Trajectory optimization matters since it can shed some seconds per each scan
=> boost measurement rate

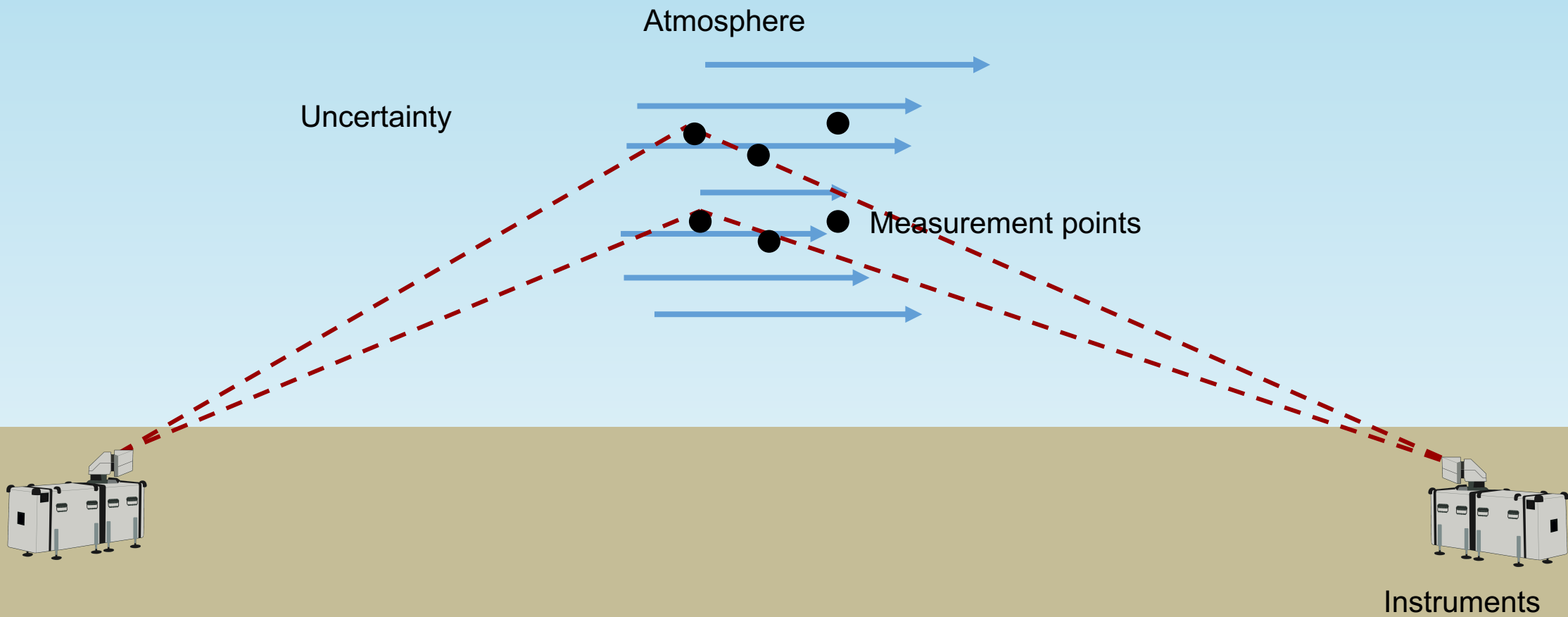
YADDUM

Following slides are taken (and modified) from presentation :

*Vasiljevic, Nikola. (2019, November). **YADDUM - Yet Another Dual-Doppler Uncertainty Model**. Zenodo. <http://doi.org/10.5281/zenodo.3551577>*

Background

- It is using an analytical model derived in 2017:
Nikola Vasiljevic, & Michael Courtney. (2017, March). ***Accuracy of dual-Doppler lidar retrievals of near-shore winds***. Zenodo. <http://doi.org/10.5281/zenodo.1441178>
- The model is based on law of propagation of uncertainties
- Simple and fast uncertainty assessment of dual-Doppler (two lidars or radars) retrievals of wind speed and wind direction
- Application: Dual-Doppler setups operating with low elevation angles and especially offshore

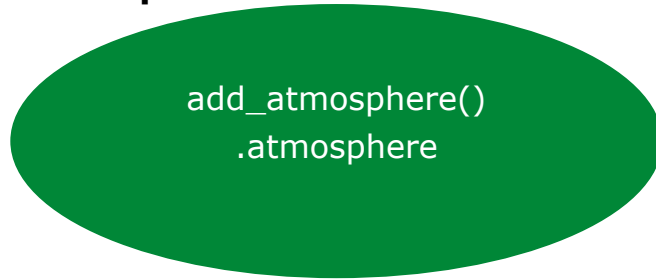


Basic entities

1. Atmosphere
2. Measurement point(s)
3. Instrument(s)
4. Uncertainty

Classes and their relations

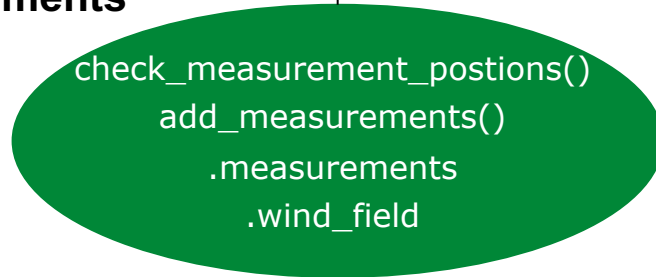
Atmosphere



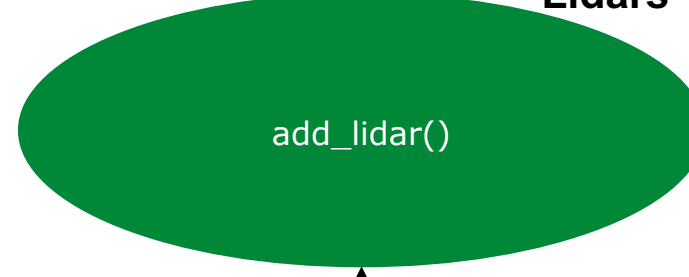
Instruments



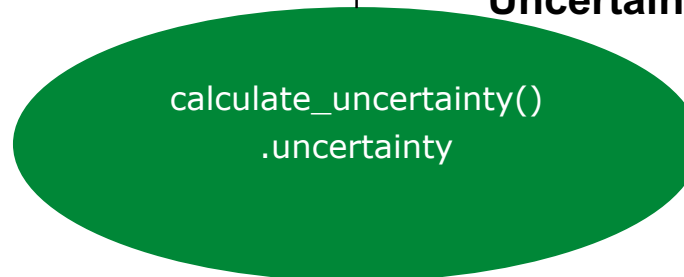
Measurements



Lidars



Uncertainty



.wind_field

.uncertainty

xarray datasets with cf standard names and certain metrological and wind energy terms.

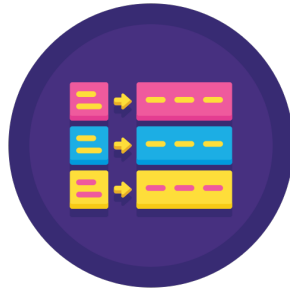
- Not listing args and kwargs
- Not listing private methods and attributes

Workflow

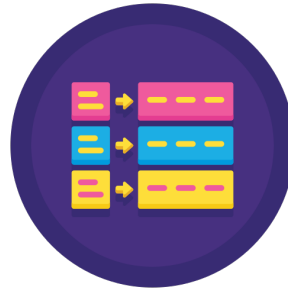
1. `add_atmosphere(atmosphere_id, model, model_parameters)`
 - *Currently the method support only wind power law profile as the 'atmospheric model'*
2. `add_measurements(measurements_id, category, utm_zone, **kwargs)`
 - *Currently the method support adding either arbitrary set of points or 2D mesh of points*
3. `add_lidar(instrument_id, position, category, **kwargs)`
 - *Currently the method allow addition of single lidar per time*
4. `calculate_uncertainty(instrument_ids, measurements_id, atmosphere_id, model)`
 - *Currently radial speed uncertainty and dual-Doppler uncertainty models are supported*

Dictionaries and xarray objects

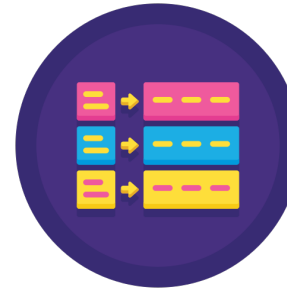
1. `add_atmosphere()`, `add_measurements()` and `add_lidar()` create three dictionaries:



atmosphere



measurements



instruments

2. `calculate_uncertainty()` creates two xarray datasets:



wind_field



uncertainty

YADDUM is ...

- Using only `xarray` and `numpy` packages
- Fully documented (numpy docstring)
- Versioned on [Github](#)
- Persisted on [Zenodo](#)
- Available as a conda package through [Anaconda cloud](#)
- Or on [binder](#) for direct manipulation without any installation

example_1

https://notebooks.gesis.org/binder/jupyter/user/niva83-yaddum-xvfjzhws/notebooks/examples/example_1.ipynb

Visit repo

Copy Binder link

Jupyter example_1 (unsaved changes)

FileEditViewInsertCellKernelWidgetsHelp

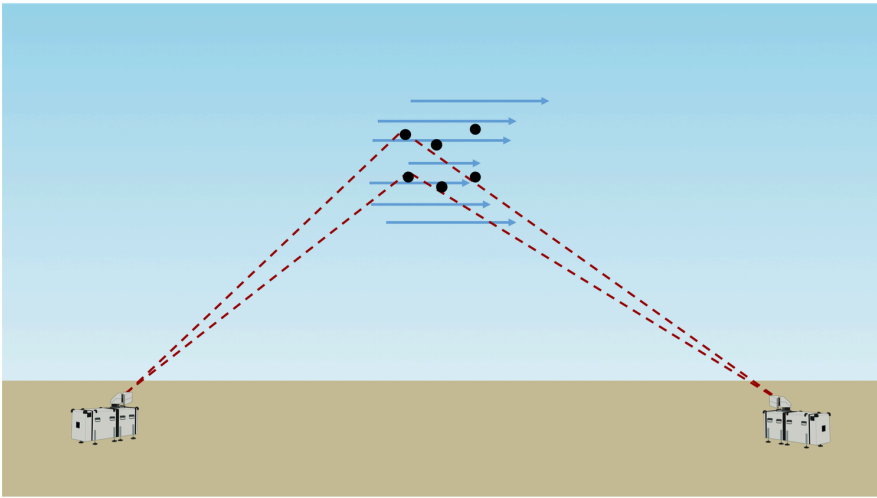
Not Trusted

Python 3

release v0.2.0 DOI 10.5281/zenodo.3580749 license BSD Donate Buy me a coffee

YADDUM: Yet Another Dual-Doppler Uncertainty Model

YADDUM is focused on delivering a simple yet effective dual-Doppler uncertainty model. This package is based on the [dual-Doppler uncertainty model](#) developed by [Nikola Vasiljevic](#) and [Michael Courtney](#). The model is based on the [law of propagation of uncertainties](#). A full mathematical description of the model is enclosed in the YADDUM docstring. Currently, YADDUM is applicable for [wind lidars](#) and [radars](#).



YADDUM contains five classes (see image below) which are: *Atmosphere*, *Measurements*, *Instruments*, *Lidars* and *Uncertainty*. However, users only interacts with the class *Uncertainty* as this class inherits the properties of the remaining four classes.

Atmosphere

```
add_atmosphere()
```

Instruments

```
check_instrument_position()
```

Try it your self < this is clickable

Work beyond 2019...

1. `add_atmospheric_models()`
 - Extend catalogue of atmospheric models
2. `add_measurements()`
 - Extend capabilities to LOS, RHI, Fov, etc. and DBS structures of points
3. Instruments
 - Support other instrument classes (e.g., radar)
4. `calculate_uncertainty()`
 - Support other uncertainty models (single- and triple- Doppler, Monte-Carlo simulations, etc.)

mocalum

Following slides are taken (and modified) from presentation :

*Vasiljevic, Nikola. (2020, May). **mocalum: python package for Monte-Carlo lidar uncertainty modeling**. Zenodo. <http://doi.org/10.5281/zenodo.3823878>*

Features

- Fast Monte Carlo uncertainty modeling
- Simulation of single or multi lidar configuration
- Configuration of arbitrary trajectories for single and multi lidars
- Configuration of `IVAP` (sector-scan) trajectory for single lidar
- 3D or 4D / uniform or turbulent flow field generation
- Sampling of correlated or uncorrelated uncertainty terms
- Built-in 2nd order kinematic model for calculation trajectory timing
- 3D or 4D interpolation/projection of flow on lidar(s) LOS(s)
- xarray datasets enriched with metadata

Basic workflow

Create mocalum
object

Add lidar(s)

Set measurement
scenario

Sample uncertainty
contributors

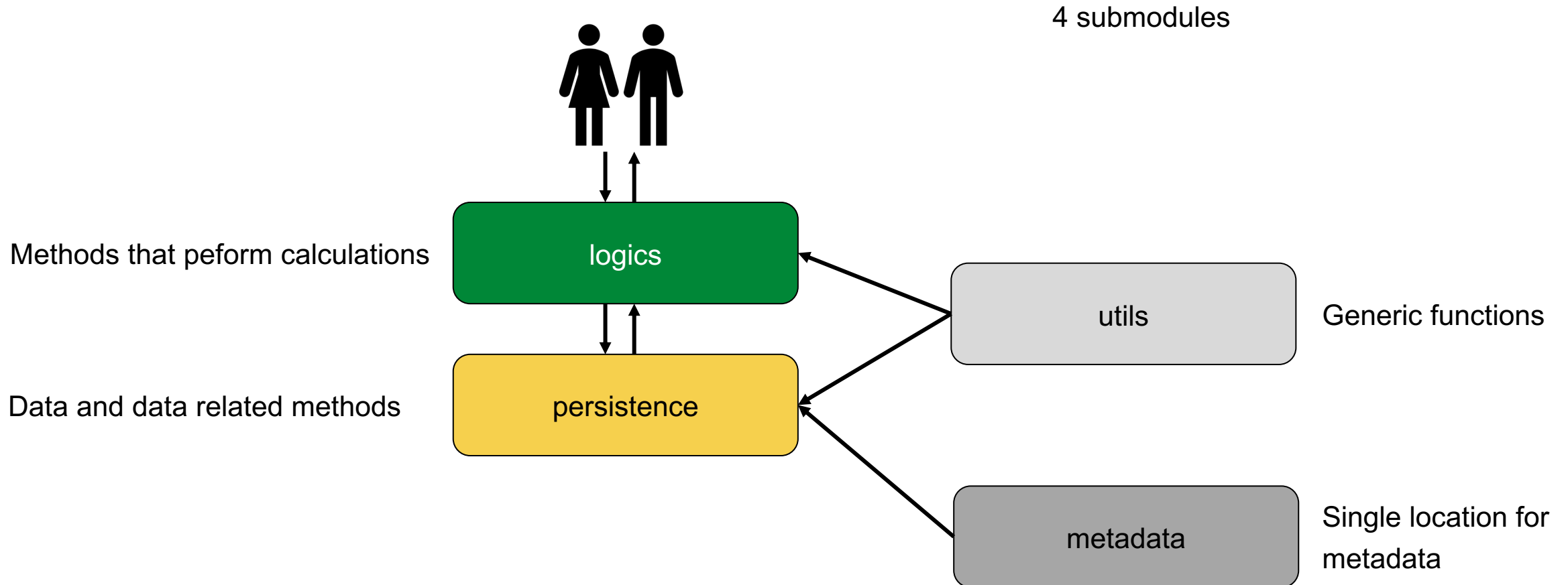
Generate flow field

Project flow on
line-of-sights

Reconstruct wind
vector

Analyze
reconstruction

mocalum architecture



mocalum object – public methods (logics submodule)

1. `add_lidar()`
2. `generate_complex_trajectory()`
3. `generate_PPI_scan()`
4. `generate_uncertainties()`
5. `generate_flow_field()`
6. `project_to_los()`
7. `reconstruct_wind()`
8. `generate_virtual_sonic()`

mocalum object – public data (persistence submodule)

Xarray DataSets (for users and mocalum methods):

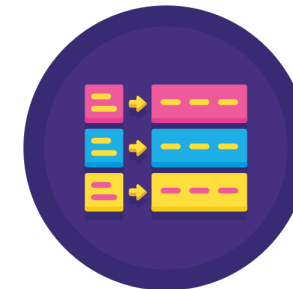
- Probing dataset
- Flow field dataset
- LOS dataset
- Reconstructed wind dataset
- Virtual sonic anemometer dataset



datasets

Python dictionaries (for mocalum methods):

- Flow model config
- Measurement config
- Bounding box for measurement points
- Bounding box for flow field generation



dictionaries

Add lidar(s)

add_lidar():

- creates measurement config

Set measurement scenario

generate_complex_trajectory() or generate_PPI_scan():

- updates measurement config
- creates bounding box for measurement points
- creates probing dataset

Sample uncertainty contributors

generate_uncertainties():

- updates measurement config
- updates bounding box for measurement points
- updates probing dataset

Generate flow field

generate_flow_field():

- creates bounding box for flow field generation
- creates flow model config
- creates flow field dataset

Project flow on line-of-sights

project_los():

- creates LOS dataset

Reconstruct wind vector

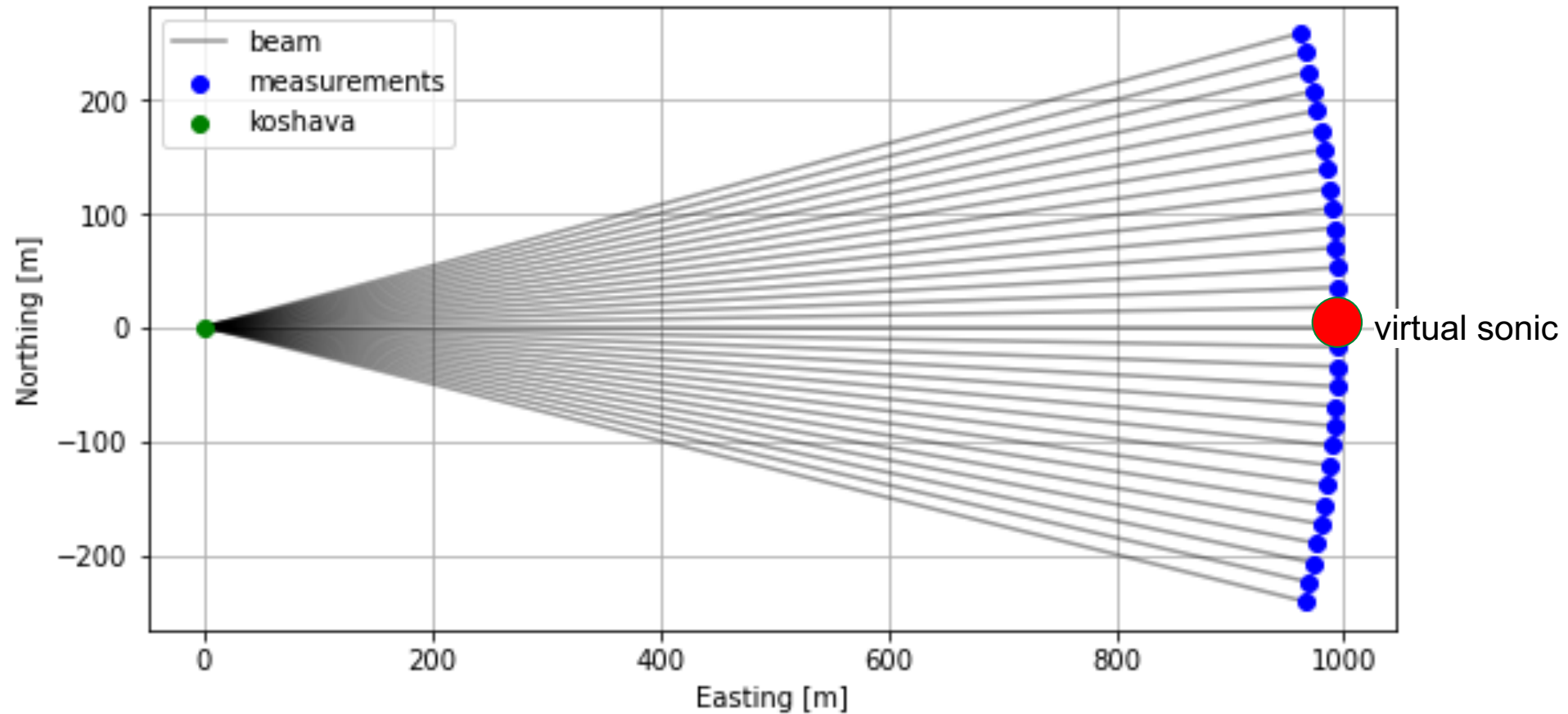
reconstruct_wind():

- creates reconstructed wind dataset

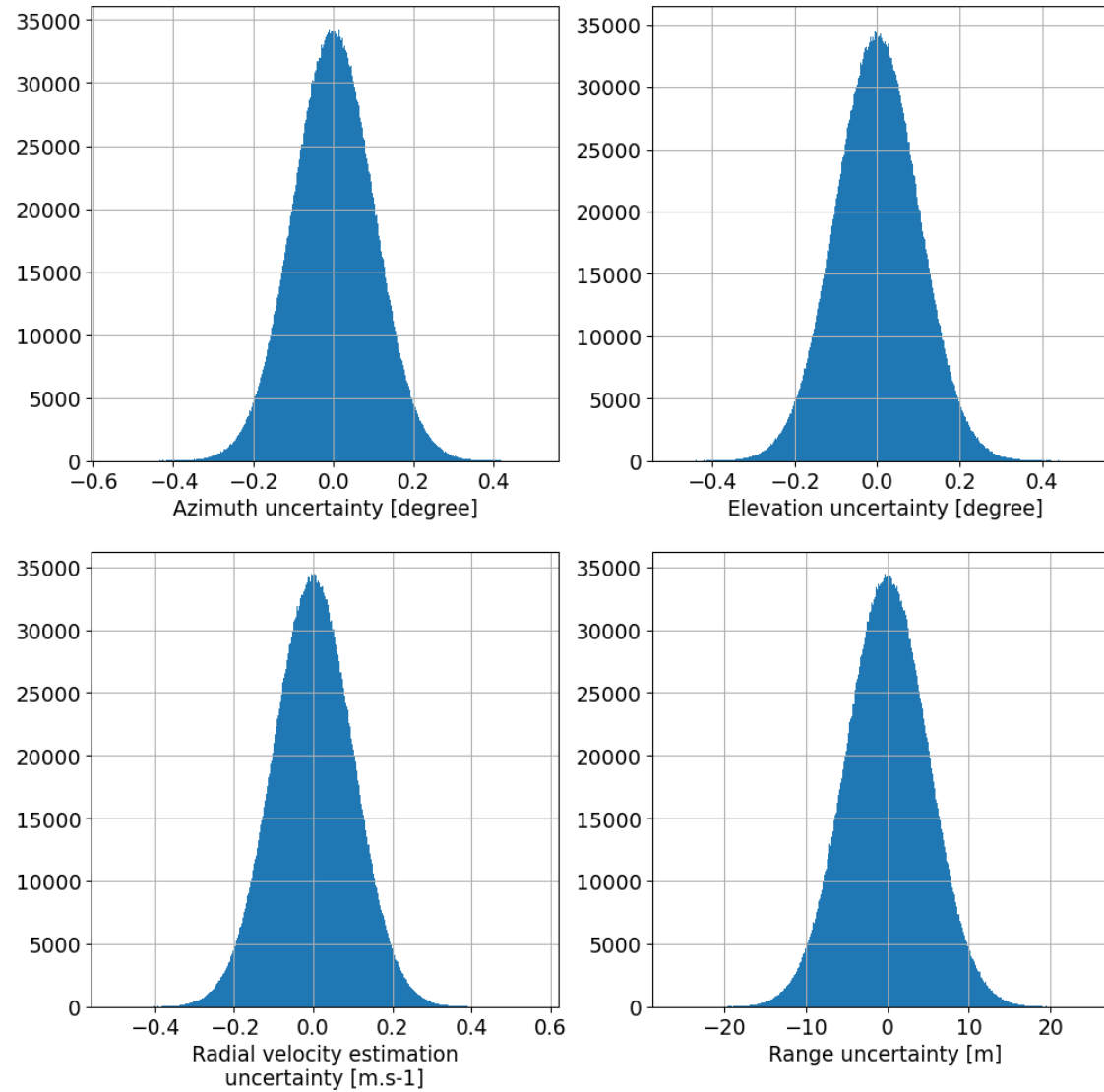
generate_virtual_sonic():

- creates virtual sonic dataset

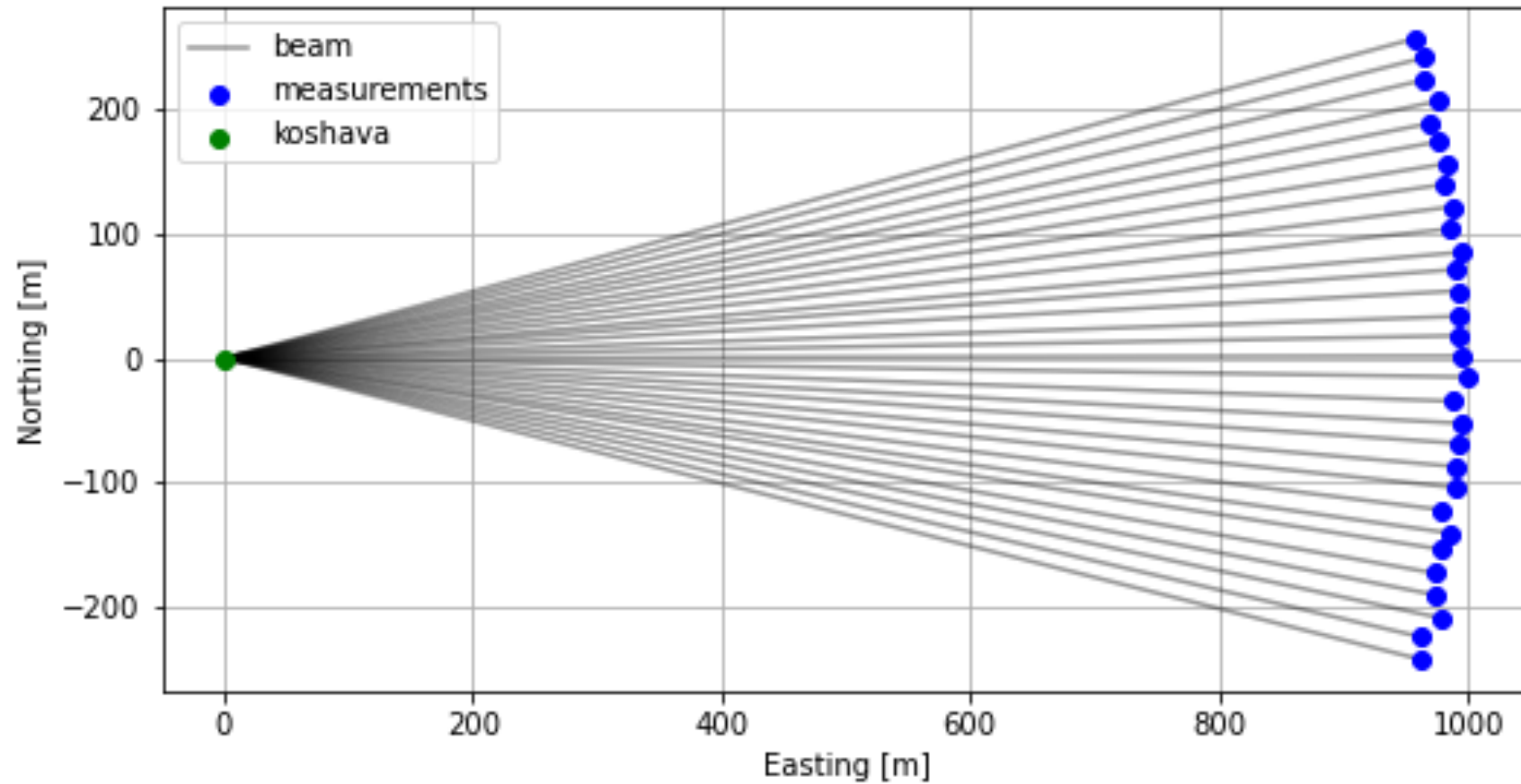
Adding lidar + config of PPI scan



Sampling uncertainties



Sampling uncertainties



Generating flow field

- **uniform flow field:** wind is only changing with height according to the [power law](#)
- **turbulent flow field:** generated using a wrapper around [pyconturb](#)

PyConTurb implementation

Start of turbulence box

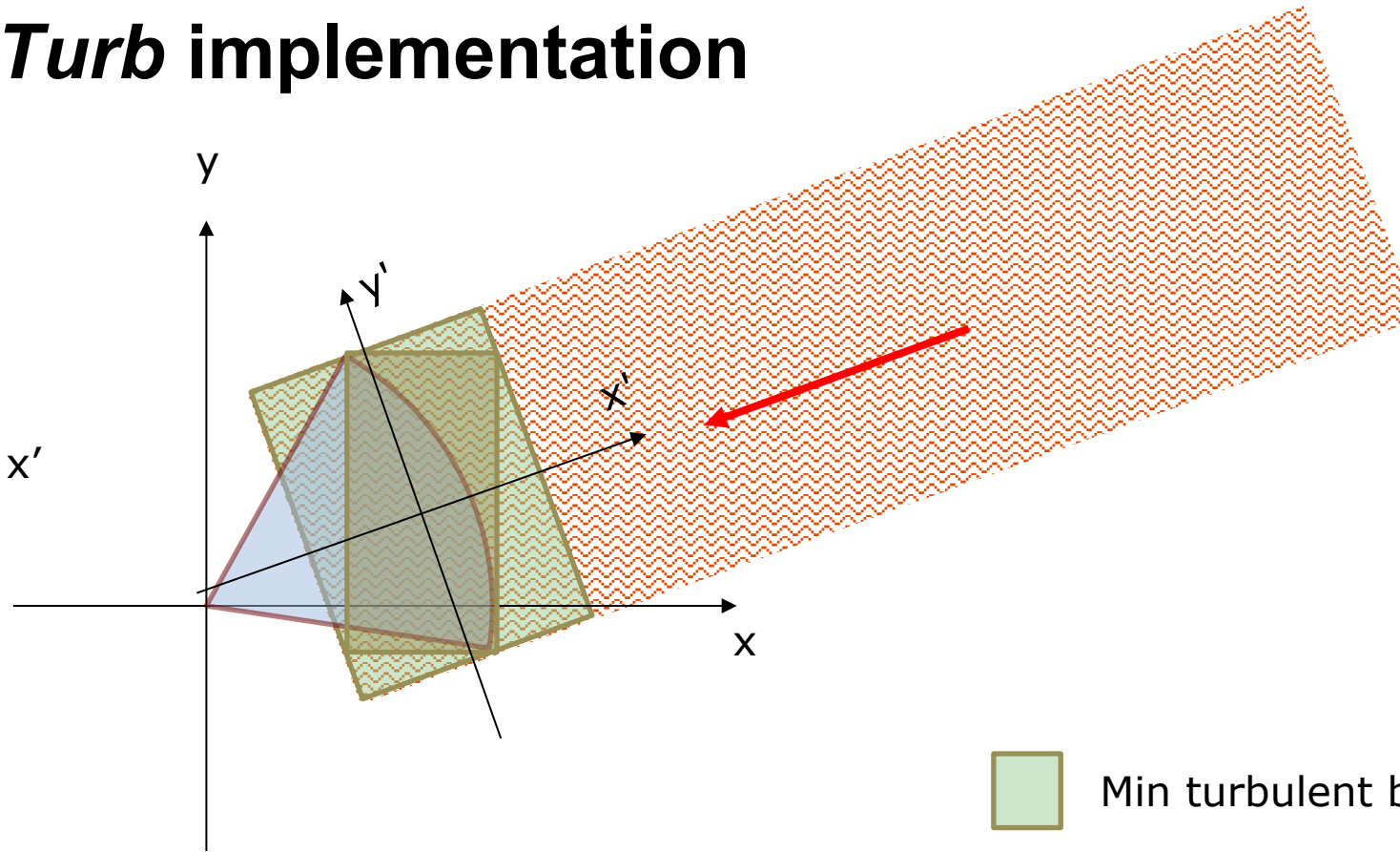
$$T=0*\Delta t$$

Replacing Time coord with x'

$$\Delta x' = WS_{\text{mean}} * \Delta t$$

y, x absolut coordinates

y', x' relative coordinates



Min turbulent box



Turbulent flow field



Bounding box around PPI arc points



PPI arc

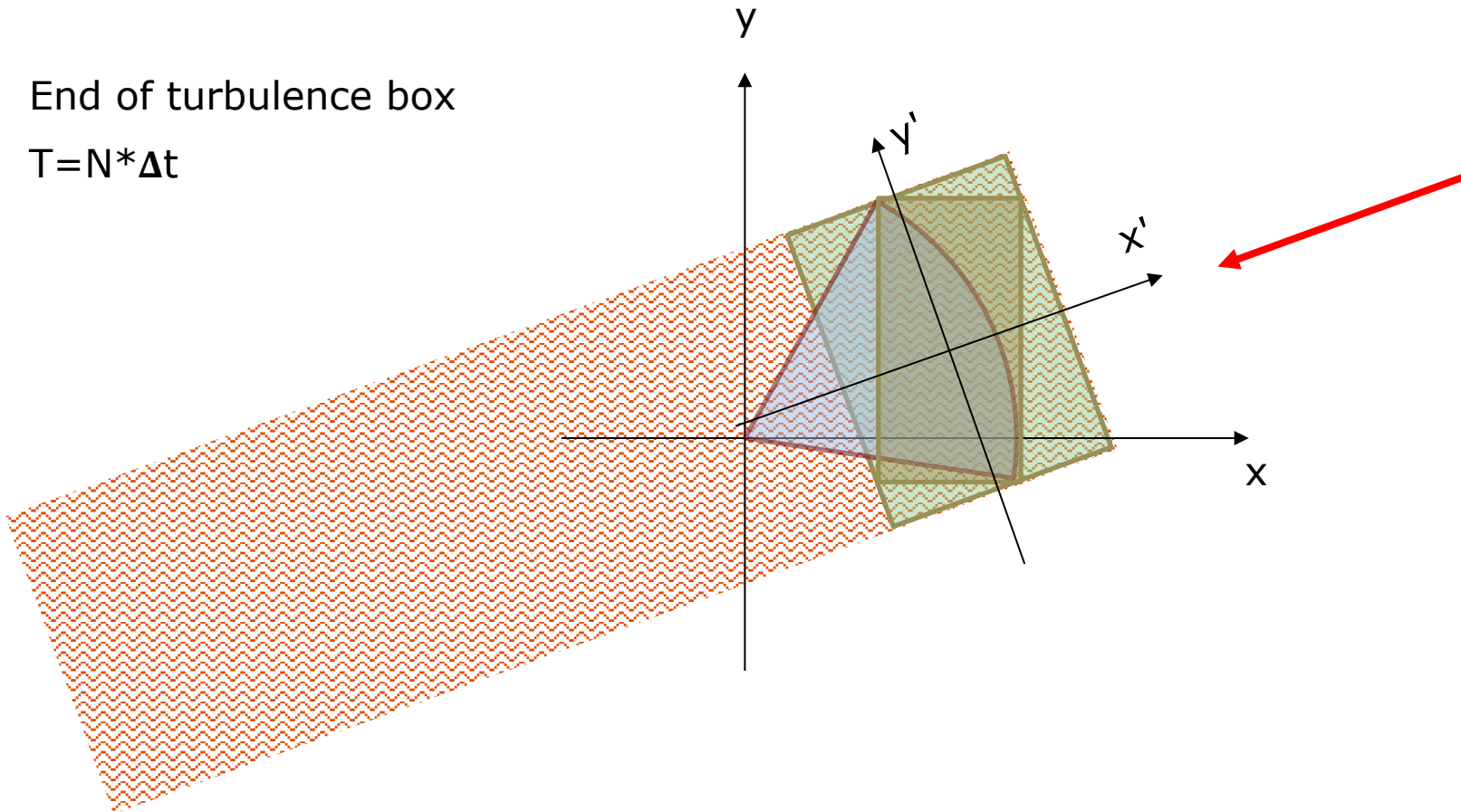


Wind direction

PyConTurb implementation

End of turbulence box

$$T = N \cdot \Delta t$$



Min turbulent box



Turbulent flow field



Bounding box around PPI arc points

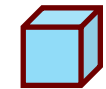




PPI arc

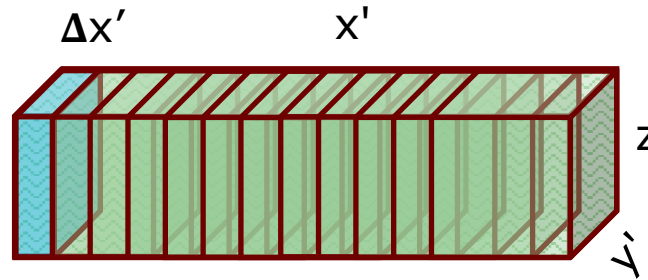


Wind direction

From 3D to 4D xarray dataset

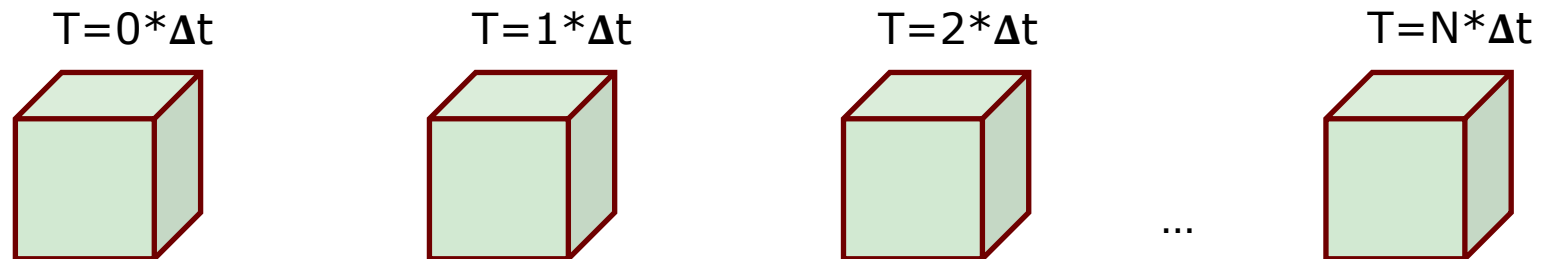
-  $\Delta x'$ array
-  Min turb box array
-  3D turbulence box

3D dataset

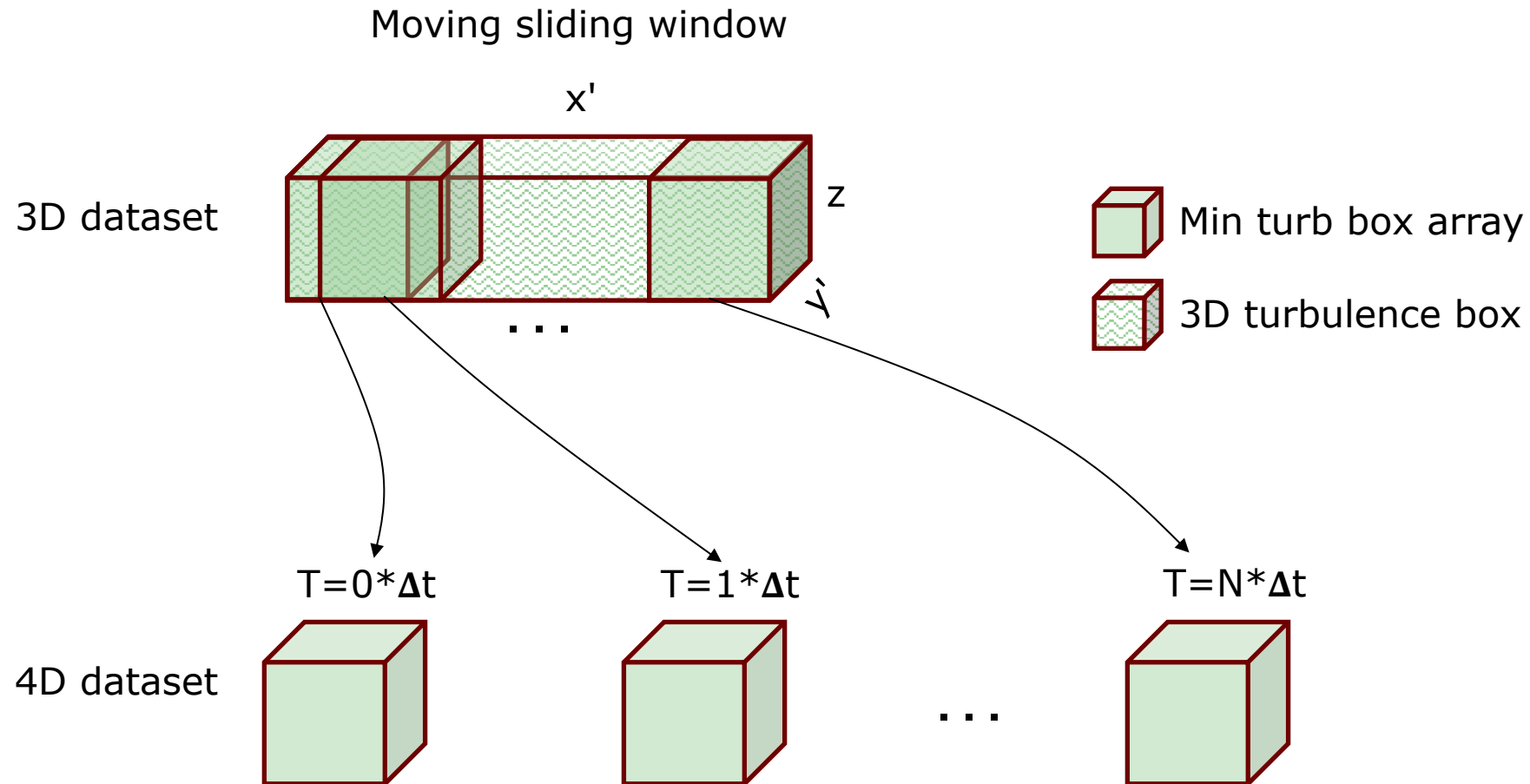


Moving sliding window

4D dataset



From 3D to 4D xarray dataset

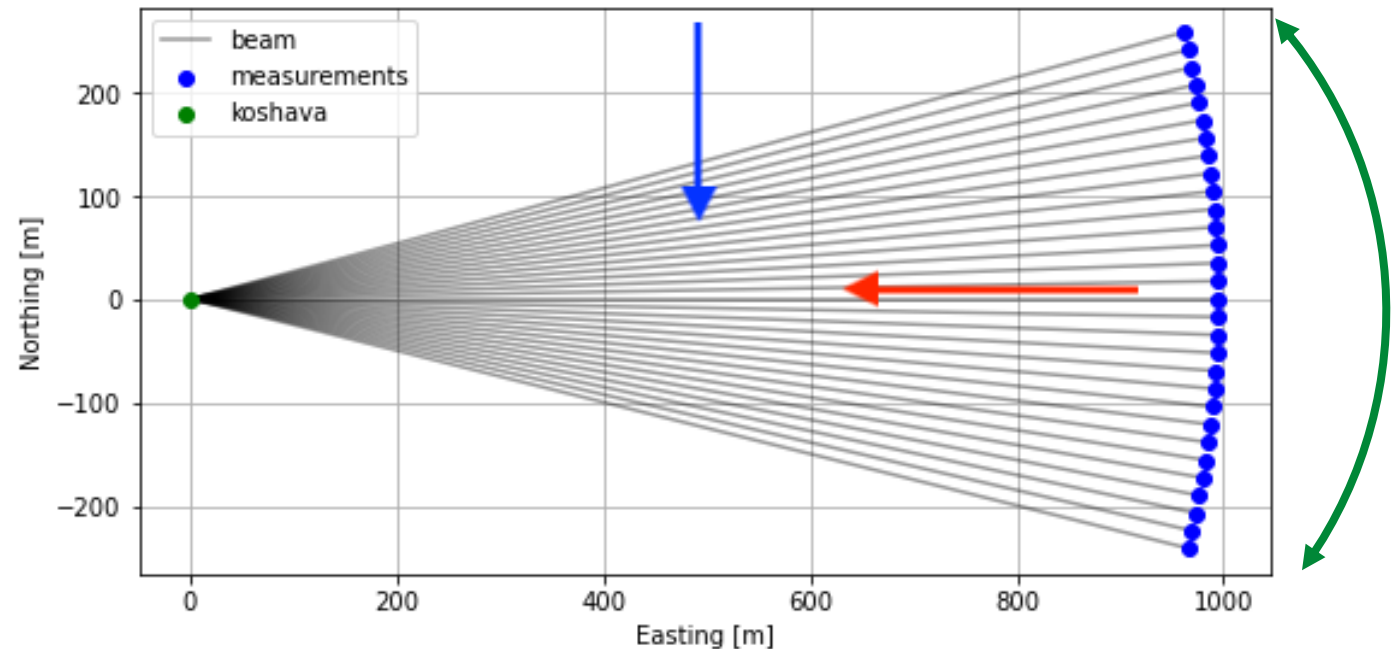


Example: single-Doppler uncertainty ([Tutorial 4](#))

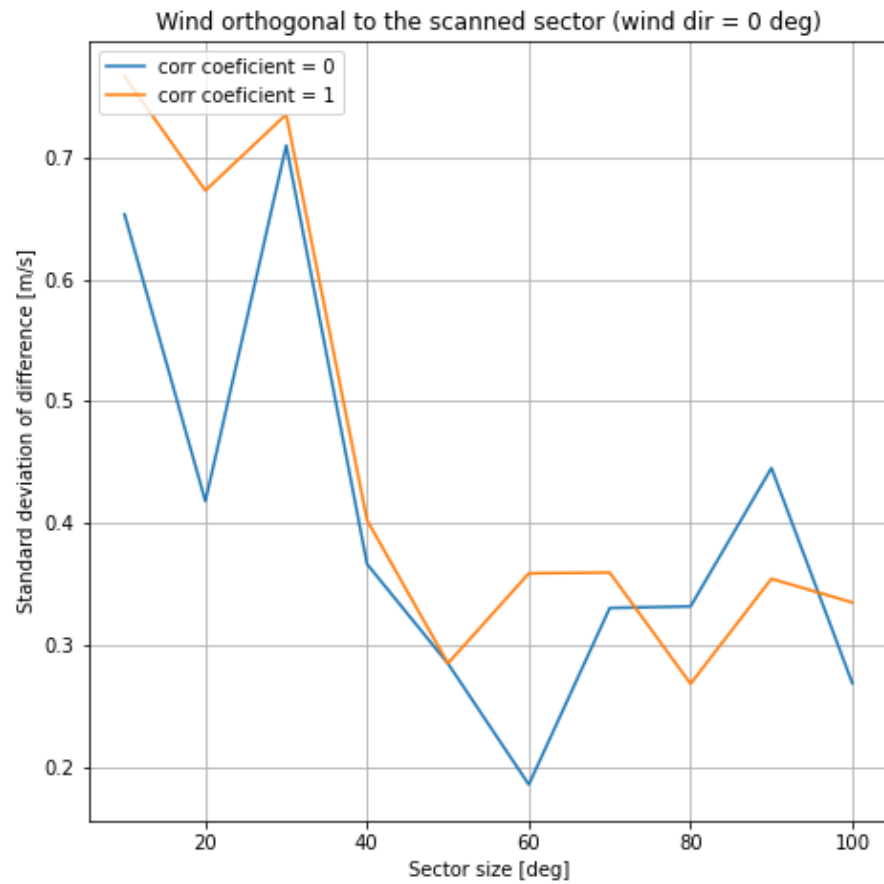
- Scanned sector varied from 10° to 100° in steps of 10°
- For two wind directions (0° - perpendicular direction, 90° - parallel direction)
- Same type of uncertainty contributors correlated/uncorrelated for all LOS
- For each simulation configuration 189000 virtual PPI scans performed
- LOS 10-min averaged prior the wind reconstruction

Total: 7.5 million virtual scans

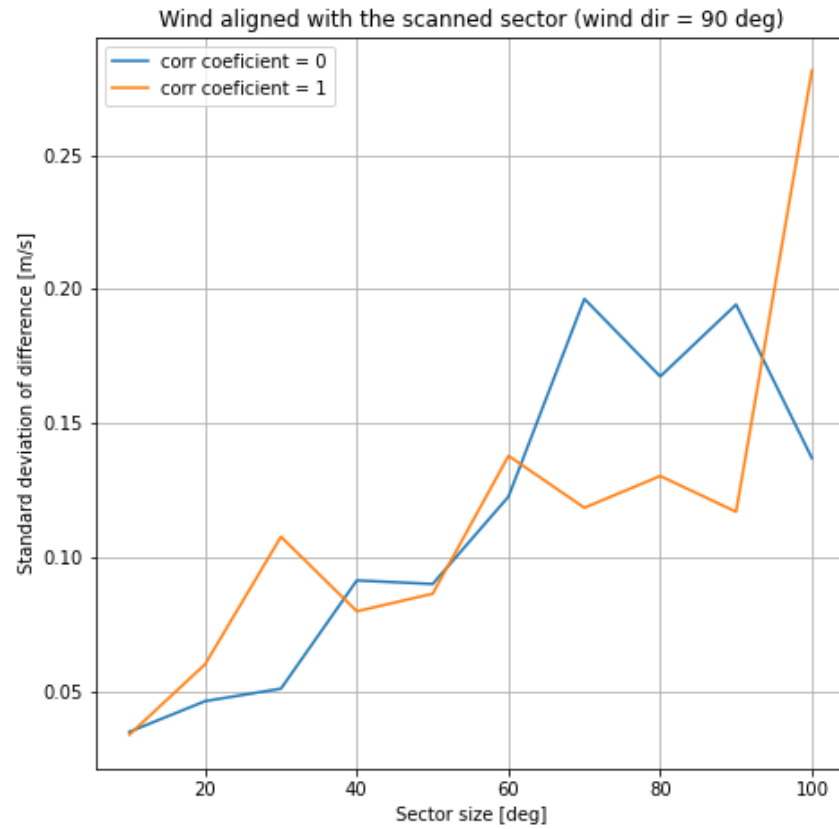
Time: 105 minutes



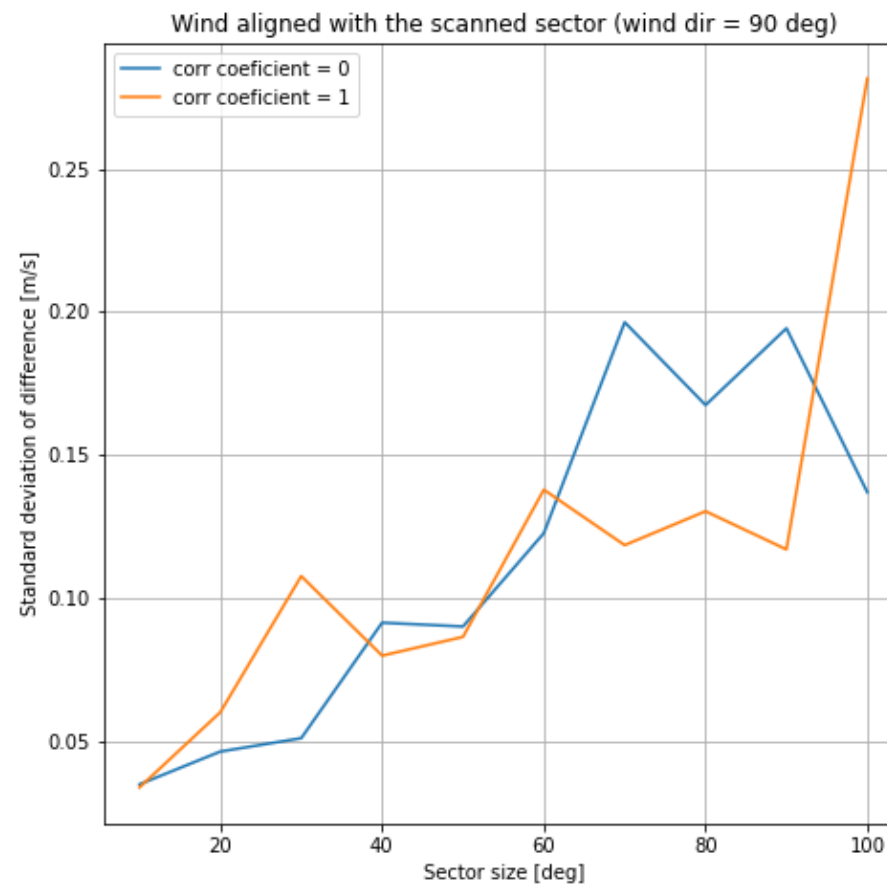
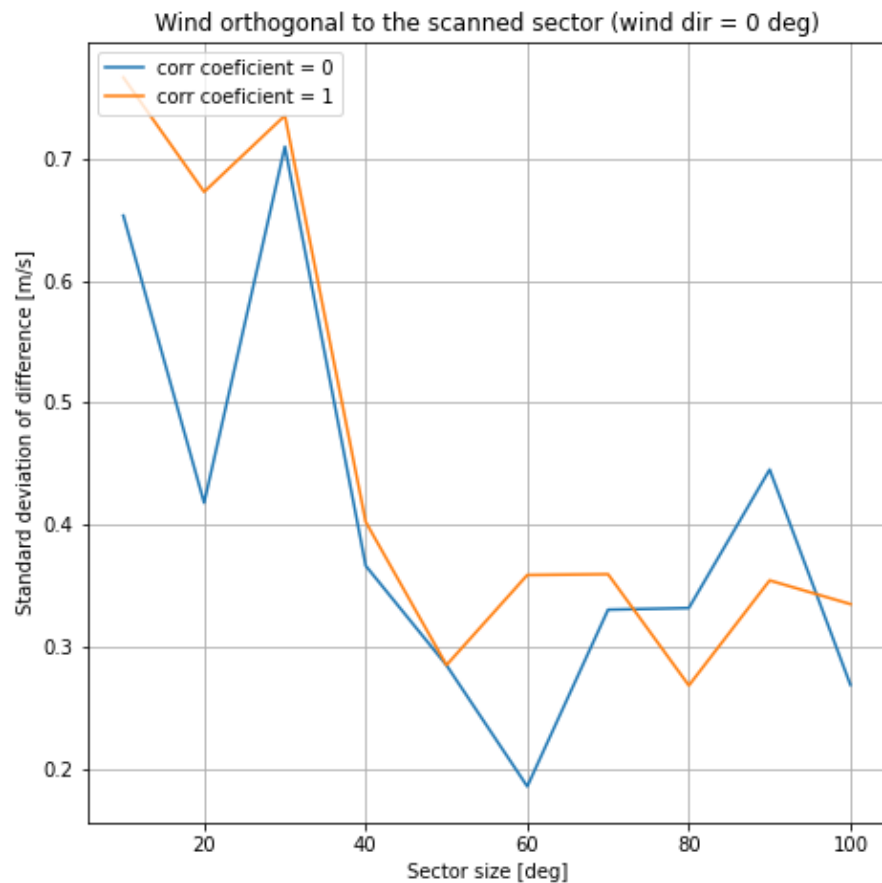
Results wind direction 0°



Results wind direction 90°



Results side by side



mocalum is

- on GitHub for:
<https://github.com/niva83/mocalum>
- persisted on Zenodo:
<https://zenodo.org/record/3822069>
- explained using jupyter-notebook based tutorials:
<https://github.com/niva83/mocalum/tree/master/examples>
- and as a web-based report:
<http://e-windlidar.windenergy.dtu.dk/reports/sd-dd-uncertainty/>

Thank you for your attention

Questions?

niva@dtu.dk

