BeFORECAST

Deliverable: Full data assimilation of experiments at Belgian offshore wind farms

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DOCUMENT CONTROL SHEET

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DOCUMENT SUMMARY
The deliverable reports on Task 5.7 of the BeFORECAST project, which focuses on full-scale data assimilation for Belgian offshore wind farms using real-world measurements. The goal is to improve wind flow reconstruction and forecasting by integrating lidar observations with large-eddy simulation (LES) models through a four-dimensional variational data assimilation (4D-Var) framework. The study adapts strong and weak 4D-Var formulations for practical application, introducing enhancements such as mean flow estimation and a receding-horizon approach to handle temporal variability. Using data from the Cloud4Wake project, the methodology reconstructs turbulent flow fields from Doppler lidar scans collected at the Mermaid concession. Results show that both strong and weak 4D-Var significantly reduce reconstruction errors compared to mean-flow-only baselines, with the weak formulation performing best due to its ability to account for model uncertainties. The work demonstrates the feasibility of lidar-driven flow assimilation for offshore wind farms and has been submitted for dissemination at TORQUE2026.

Table of Contents

1 Introduction

The current document presents the research activities conducted under Task 5.7, “Full data-assimilation of experiments at Belgian offshore wind farms”, within the BeFORECAST project. The objective of this task is to advance full-scale data assimilation capabilities for offshore wind farms based on real measurement data.

Reliable wind forecasts are essential to guarantee a safe and cost-efficient operation of wind farms. They enable more accurate power production estimates and support grid balance under changing atmospheric conditions, in response to the inherent intermittency of the wind resource. A key challenge lies in reconstructing the atmospheric boundary layer (ABL) flow – particularly its turbulent, three-dimensional structure – from the limited observations typically available, such as sonic anemometers or pulsed light detection and ranging (lidar) [1,2].

Data assimilation provides a powerful framework to address this challenge by merging observational data with model predictions in a statistically consistent manner. At KU Leuven, a four-dimensional variational data-assimilation (4D-Var) framework has been developed based on large-eddy simulation (LES) [3,4]. As part of Task 3.3, this framework was extended into a weakly-constrained 4D-Var algorithm that explicitly accounts for model uncertainties in the LES formulation through an additional error term [5]. Here, we aim to apply this methodology to real-world measurements from the Belgian offshore wind farms, moving towards realistic lidar-driven flow reconstruction.

The report is organized as follows. Section 2 first describes the experimental dataset that was used throughout this task. Section 3 then describes an extension of the 4D-Var methodology towards practical data and reports some results and a discussion thereof, followed by Section 4, which provides an overview dissemination activities related to this deliverable.

2 Experimental dataset

Task 5.7 aimed at the full data assimilation of the measurements campaigns from Work Package 1 of the BeFORECAST project. However, as the project progressed and methods were developed, it became clear that the turbulent flow reconstruction algorithms from WP3 would be better demonstrated on experimental data with a high spatial coverage. Instead, we therefore resort to the experimental data obtained as part of the Cloud4Wake project [6]. Specifically, we make use of measurements collected by a 3D scanning Doppler lidar (Vaisala WindCube Scan) operating in plan-position-indicator (PPI) mode at a low elevation. The measurement campaign took place from 5 June to 24 August 2025, with the lidar installed on the transition piece of turbine MC2 in the Mermaid concession, approximately 50 km off the Belgian coast (see Figure 1).

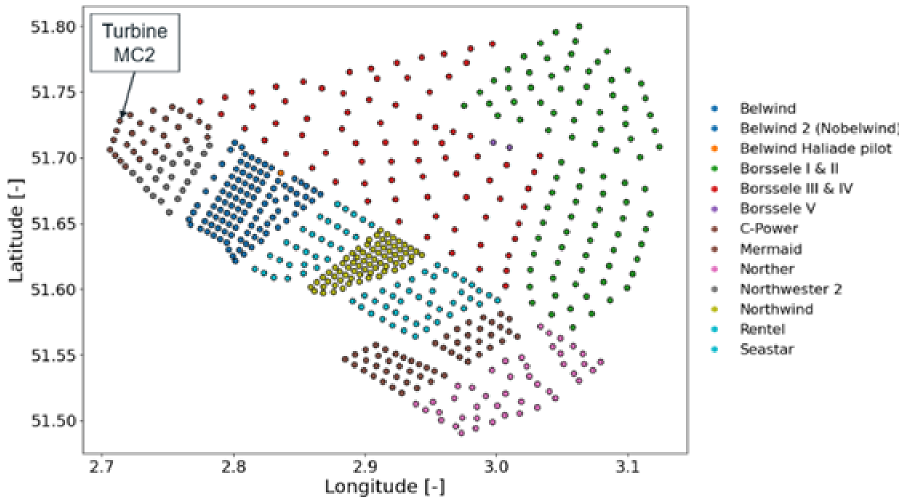


Figure 1 Lidar location on turbine MC2 within the Belgian wind farm cluster.

As an initial step, the analysis focuses on periods characterized by quasi-stationary wind direction and neutral atmospheric stratification. Suitable intervals were identified using temperature, wind speed, and wind direction data from the Westhinder measuring pile, located roughly 40 km southwest of the lidar site [7]. Based on these criteria, the period 10 June 2025, 00:00–12:00 UTC was selected for detailed investigation.

Figure 2a shows an example of the raw line-of-sight (LOS) measurement from a single scan with a gate length of 75 m. To enhance data quality, a carrier-to-noise ratio (CNR) threshold filter was applied, as illustrated in Figures 2b–c, which display the CNR and the corresponding filtered LOS data, respectively.

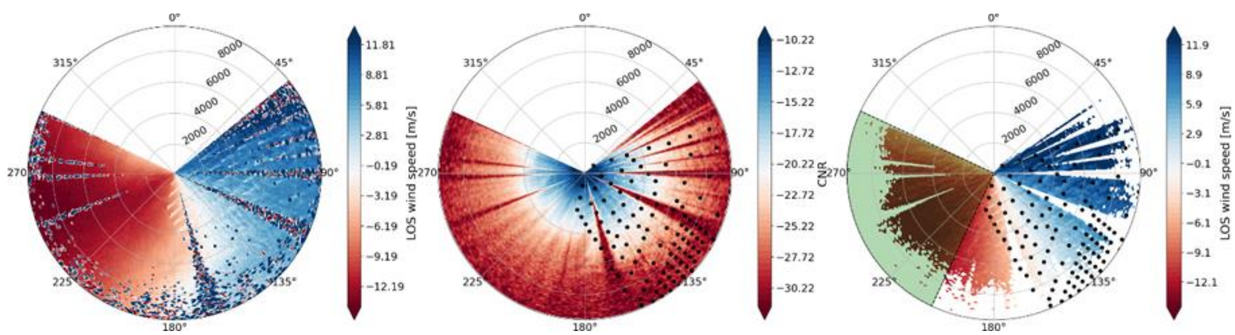


Figure 2 LOS wind speed, CNR and filtered LOS wind speed for an example lidar scan.

Finally, as this study focuses on the reconstruction of the freestream flow, only the azimuthal sector free of turbine wakes and other flow disturbances (indicated in green in Figure 2) was retained for further analysis.

3 Practical strong and weak 4D-Var for flow reconstruction

The data assimilation framework used in this task builds on the LES-based strong and weak 4D-Var formulations developed by Alreweny et al. (2024, 2025) [4,5]. To adapt the methodology for application with real lidar measurements, several extensions have been introduced. In particular, the formulation has been updated to also reconstruct the mean flow component, which in earlier studies was assumed to be known a priori. In addition, the 4D-Var has been embedded within a receding-horizon framework to allow flow reconstruction over extended time periods, while accounting for potential variations in wind speed and wind direction.

The updated processing and assimilation pipeline is described in Section 3.1, followed by Section 3.2, which presents some results including reconstructed flow fields and related analyses.

3.1 4D-Var methodology

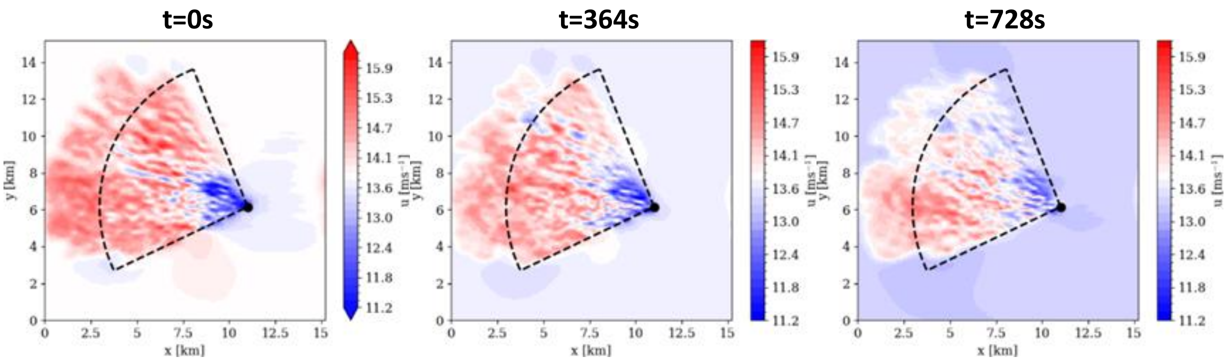
Following the maximum a posteriori approach in Refs. [4,5], the 4D-Var is formulated as a PDE-constrained optimization problem. The objective is to reconstruct an initial flow field that minimizes the discrepancy between the simulated and observed lidar data over an assimilation horizon T, subject to the LES flow model for a neutrally stratified ABL. To accelerate the convergence, the problem is regularized based on a prior in the form of the analytical Hunt-Graham-Wilson (HGW) correlation tensor, which models the spatial correlations in the background flow [8]. In the weakly constrained formulation, an additive model error term is also optimized to account for uncertainties arising from the LES model.

To handle temporal variations in the background wind direction and wind speed, a hierarchical procedure is introduced. First, the mean wind speed and direction are estimated within each assimilation window by minimizing the reconstruction error under the assumption of a logarithmic profile. The resulting profile is then imposed as the background mean flow (i.e. a regularization for the mean flow) in the subsequent 4D-Var optimization. This step was found to be crucial for achieving physically consistent reconstructions, as inaccurate mean profiles tend to cause artificial distortions in the reconstructed turbulent fluctuations within the lidar observation region.

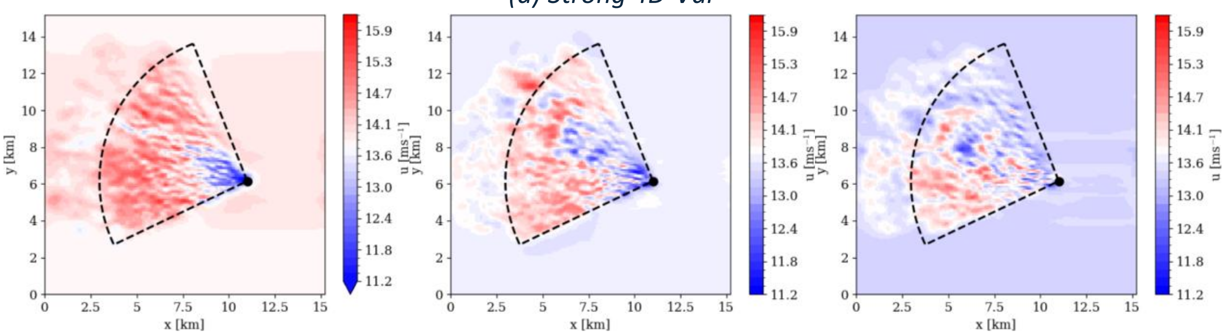
The overall assimilation is then performed in a receding-horizon fashion, where the total assimilation period is subdivided into multiple (potentially overlapping) assimilation windows. Withing each window, the mean wind profile is first determined as described above, followed by the reconstruction of the turbulent flow field through the 4D-Var procedure. This approach assumes that the wind direction and freestream wind speed remain approximately constant within the assimilation window – an assumption justified by the relatively short window durations (typically only up to 200s) compared to the slower variability of these quantities over longer timescales.

3.2 Reconstruction results

Figure 3 presents selected snapshots of the reconstructed turbulent flow fields obtained using both the strongly and weakly constrained 4D-Var algorithms over a total assimilation period of approximately 15 minutes. In the receding-horizon setup, each assimilation window spans 227 s (covering two lidar scans) with an overlap of 45 s (corresponding to one lidar scan), resulting in an update time of 182 s.



(a) Strong 4D-Var



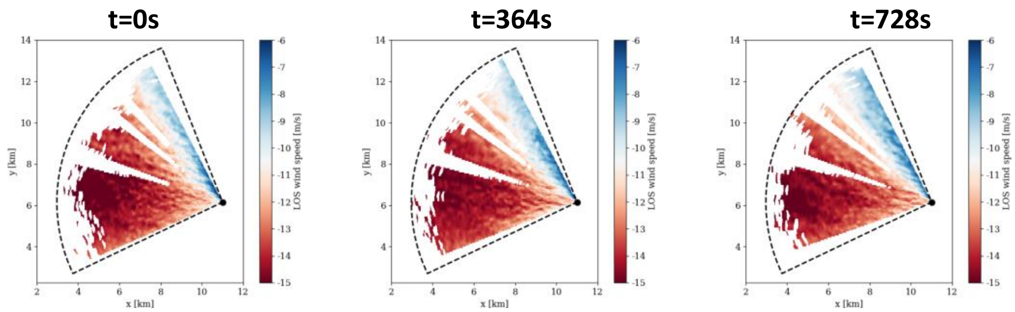
(b) Strong 4D-Var

Figure 3 Reconstructed streamwise velocity at z=75m using 4D-Var.

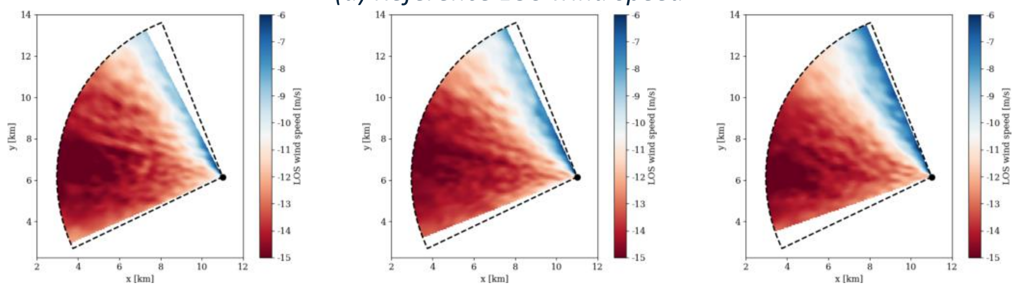
Within the lidar scanning region, the LES-based reconstructions reveal coherent turbulent flow structures, whereas outside this region, the flow smoothly transitions to the reconstructed logarithmic background profile. For clarity, the reconstructed flow fields in Figure 3 have been rotated relative to Figure 2 to approximately align the mean wind direction with the x-axis. Visually, both the strong and weak 4D-Var formulations yield similar flow patterns within the scanning region.

In the absence of full-field reference data, the accuracy of the reconstruction is assessed based on the reconstruction error between the a posteriori reconstructed LOS wind speeds and the raw LOS measurements. Figure 4 shows the measured LOS data, the reconstructed LOS and LOS reconstruction error for both strong and weak 4D-Var. For comparison, Figure 5 presents the corresponding results obtained when using only the reconstructed mean (logarithmic) flow without turbulence reconstruction. Both 4D-Var approaches substantially reduce the reconstruction error compared to the mean-flow-only baseline, demonstrating the potential of the approach. This improvement is further quantified by the accumulated reconstruction error per assimilation window, summarized in Table 1.
Interestingly, weak 4D-Var outperforms the strong variant in terms of the a posteriori reconstruction error. A similar trend was reported in simulation environment by Alreweny et al. (2025) [5]. This result is expected, since real-world flow dynamics deviate from the idealized LES model, and the weak formulation explicitly accounts for such model-form uncertainties through the additional error term.

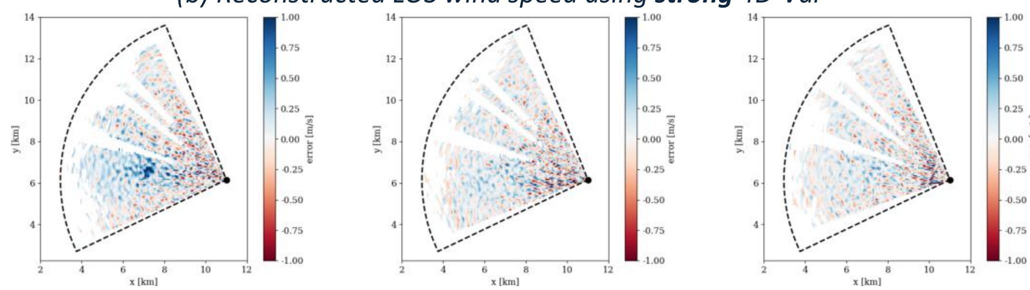
The practical implementation of weak 4D-Var is made feasible by the efficient parallelization within our LES solver and some clever modeling assumptions, such as the time decorrelation in HGW regularization of the background term. These features together ensure a computationally efficient yet physically robust reconstruction process, suitable for real-world lidar-based flow assimilation.



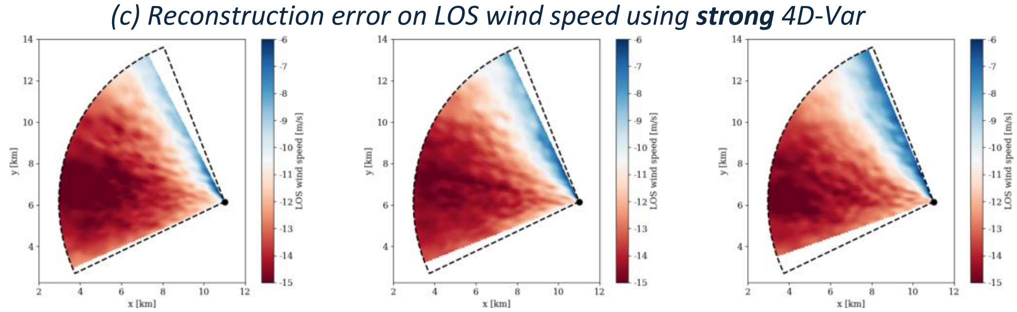
(a) Reference LOS wind speed



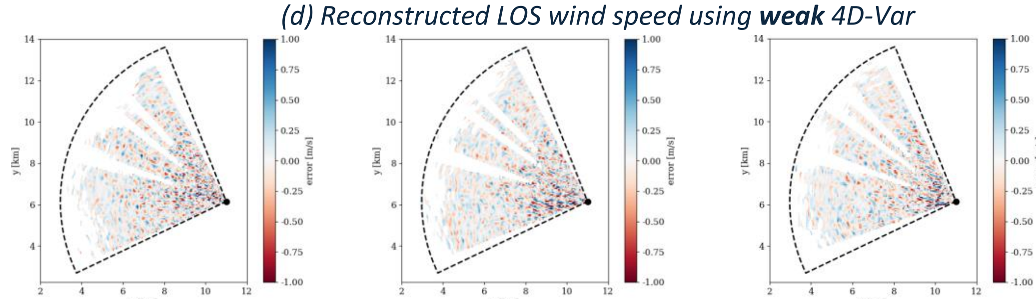
*(b) Reconstructed LOS wind speed using **strong** 4D-Var*



*(c) Reconstruction error on LOS wind speed using **strong** 4D-Var*

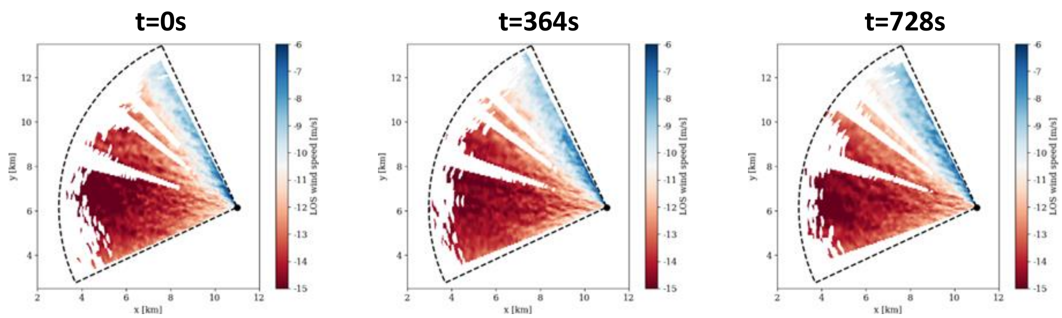


*(d) Reconstructed LOS wind speed using **weak** 4D-Var*

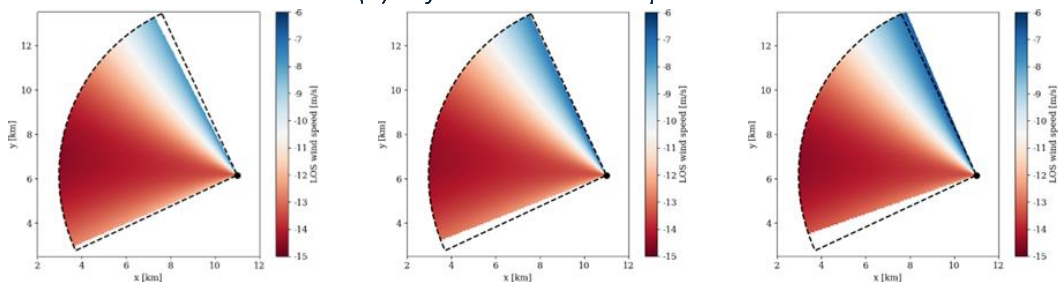


*(e) Reconstruction error on LOS wind speed using **weak** 4D-Var*

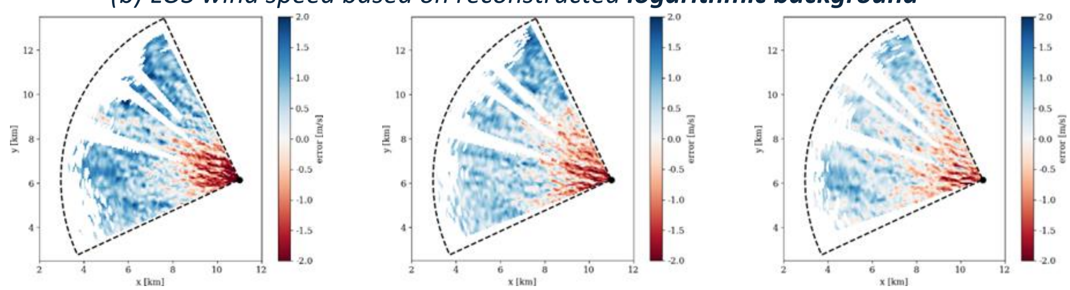
Figure 4 Reference and reconstructed LOS wind speed and error for 4D-Var



(a) Reference LOS wind speed



(b) LOS wind speed based on reconstructed ***logarithmic background***



(c) Reconstruction error on LOS wind speed using reconstructed ***logarithmic background***

Figure 5 Reference, reconstructed LOS wind speed and error for reconstructed logarithmic background only

Table 1 Accumulated reconstruction error over the assimilation windows (s)

	Window				
	$[0, T]$	$[T_A, T_A + T]$	$[2T_A, 2T_A + T]$	$[3T_A, 3T_A + T]$	$[4T_A, 4T_A + T]$
Strong	8.53	5.93	5.23	4.8	4.5
Weak	4.43	4.83	4.36	3.99	3.59
Mean log	44.63	38.26	28.86	22.34	19.73

4 Dissemination

The work above was submitted for TORQUE2026 (*Turbulence reconstruction from lidar measurements in the Belgian North Sea using 4D-Var and large-eddy simulation*).

5 References

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