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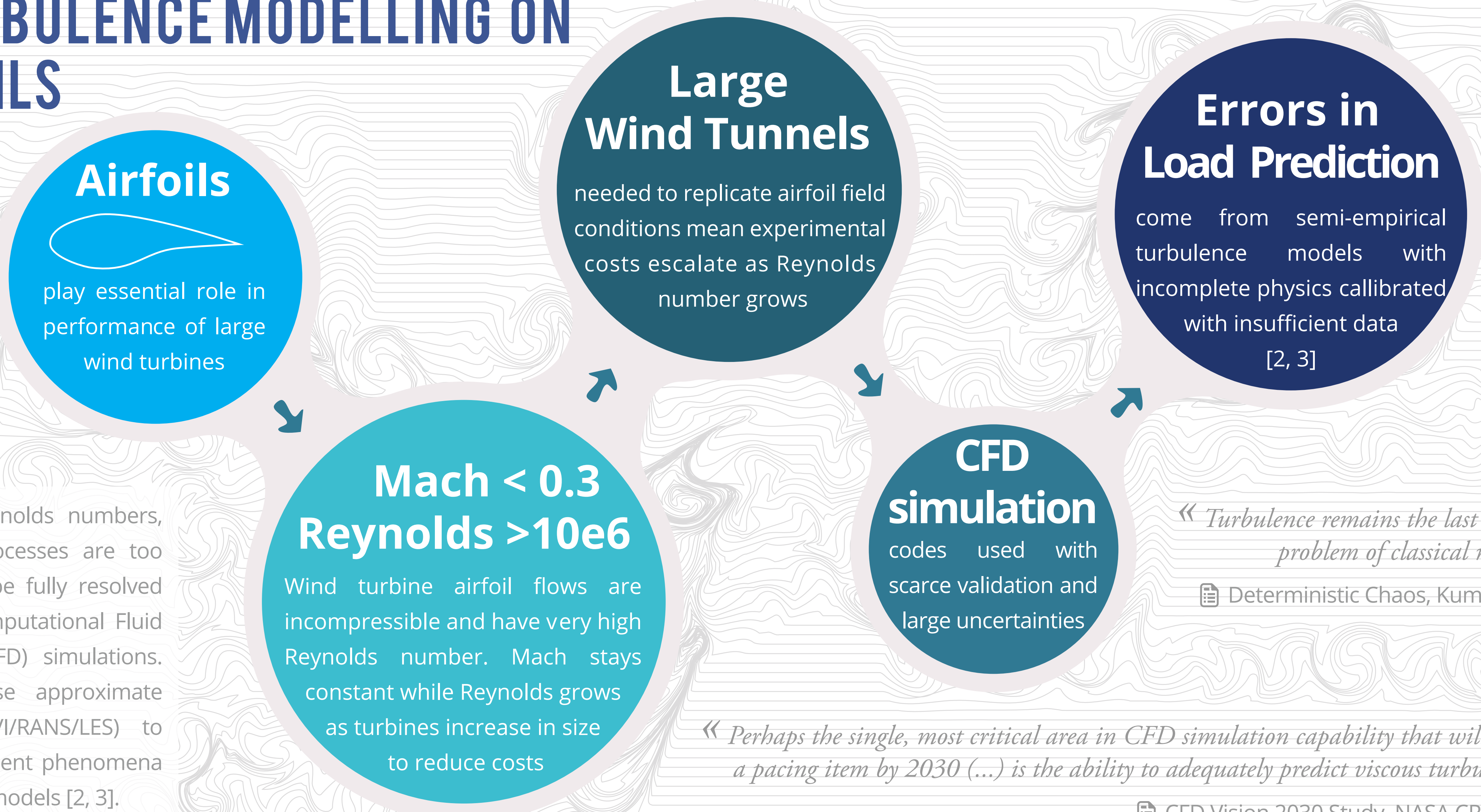
THE ISSUE WITH TURBULENCE MODELLING ON WIND TURBINE AIRFOILS

«Big whirls have little whirls that feed on their velocity, and little whirls have lesser whirls and so on to viscosity.»

Weather Prediction by Numerical Process Richardson LF, CUP

Turbulence is a complex flow process dominated by seemingly chaotic eddy motions of multiple scales. Large eddies decompose into smaller eddies of nearly random appearance, but small eddies reorganize into larger coherent structures [1].

For high Reynolds numbers, turbulent processes are too complex to be fully resolved (DNS) in Computational Fluid Dynamics (CFD) simulations. Engineers use approximate equations (VI/RANS/LES) to handle turbulent phenomena with closure models [2, 3].



«Perhaps the single, most critical area in CFD simulation capability that will remain a pacing item by 2030 (...) is the ability to adequately predict viscous turbulent flows»

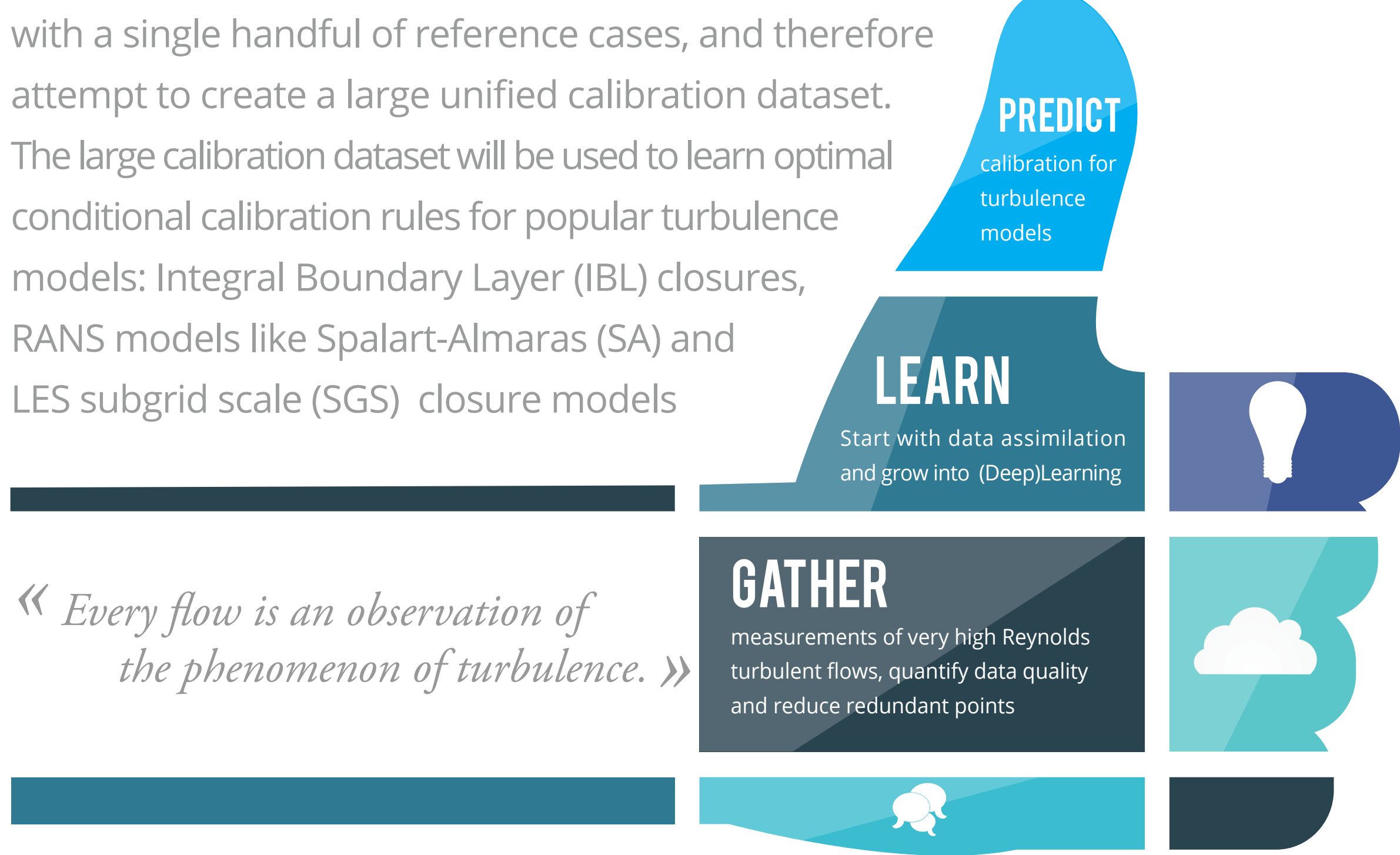
CFD Vision 2030 Study, NASA CR 2014-218178

GAZING AT CLOUDS TO UNDERSTAND TURBULENCE ON WIND TURBINE AIRFOILS

SOLUTION

ADOPT DATA RICH APPROACH TO TUNE FLOW TURBULENCE MODELS

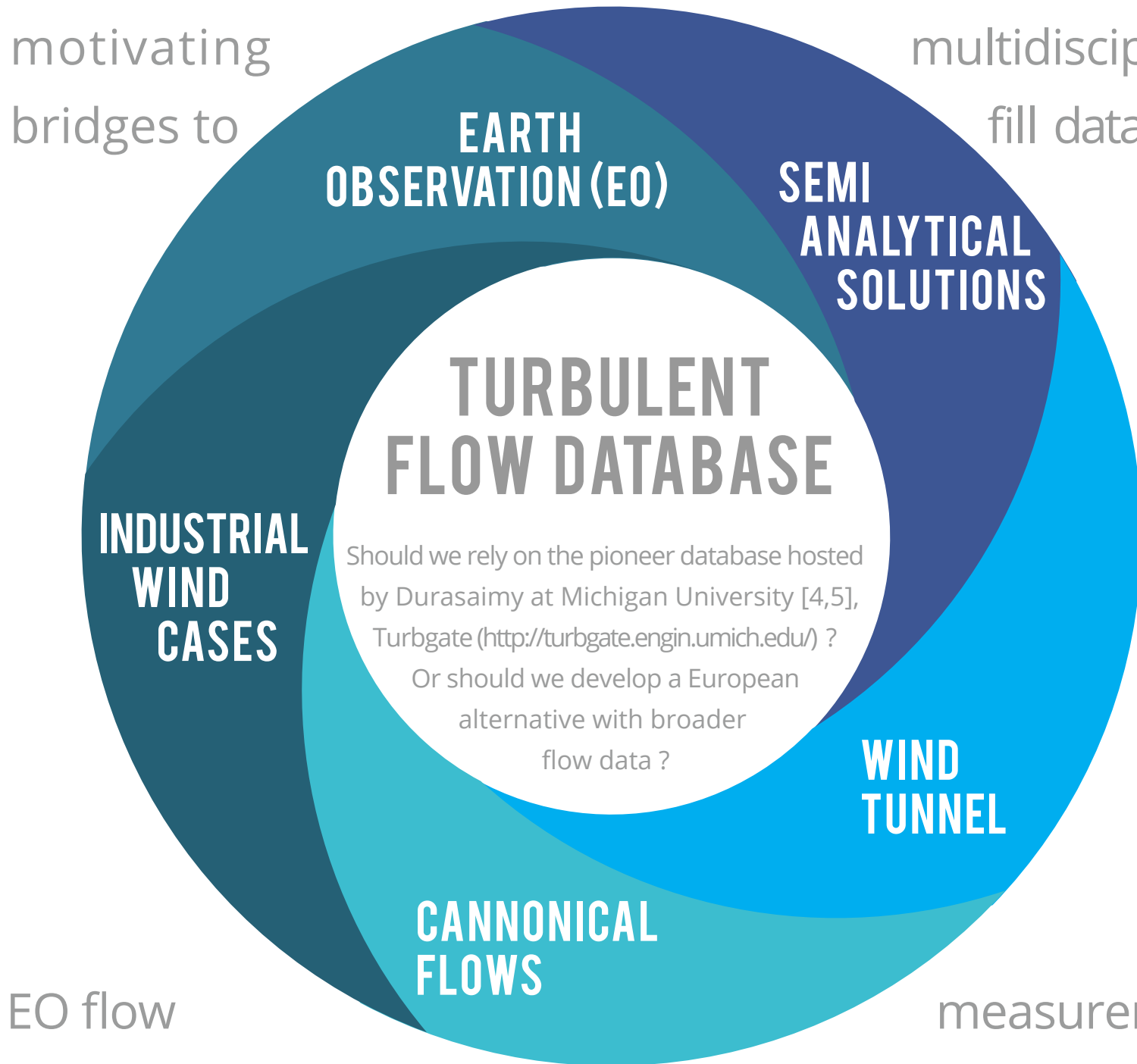
We propose to rethink the procedure for calibrating turbulence models used in popular Computational Fluid Dynamics (CFD) codes. Like Duravaisamy [4,5], we recognize that current turbulence models were calibrated with a single handful of reference cases, and therefore attempt to create a large unified calibration dataset. The large calibration dataset will be used to learn optimal conditional calibration rules for popular turbulence models: Integral Boundary Layer (IBL) closures, RANS models like Spalart-Almaras (SA) and LES subgrid scale (SGS) closure models



GATHER MEASUREMENTS OF VERY HIGH REYNOLDS FLOWS

- Flow**
Flat plate, Aerofoil
Backward Facing Step
- Flow**
Wind Turbine Wake
Power Production Loads
- Flow**
Law of the wall, e^+N theory, Isotropic Turb.
- Flow**
High Altitude Winds, Clouds, Oceanic Currents
- Flow**
Water Pipe Experiments
Taylor and Couette Flow

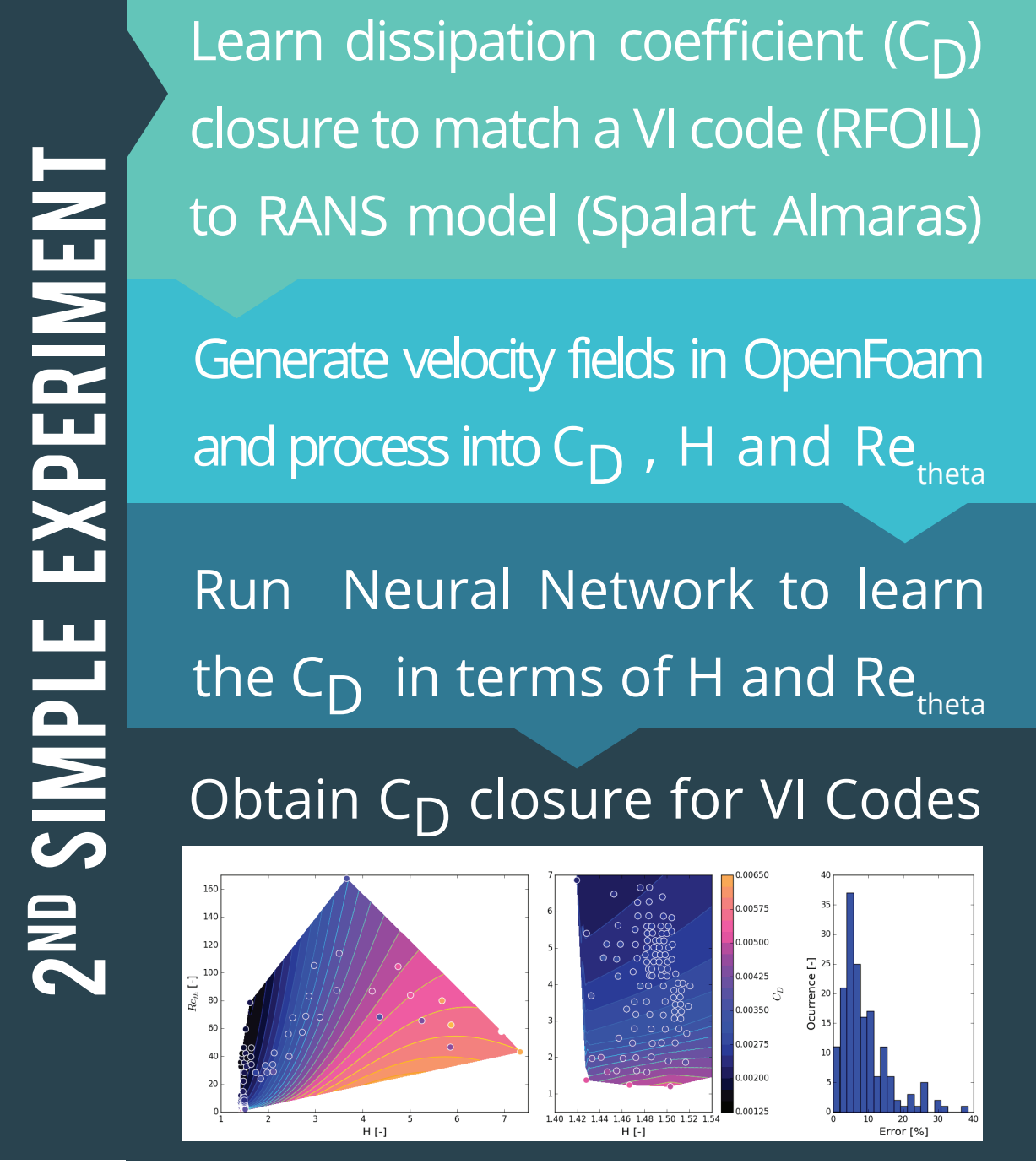
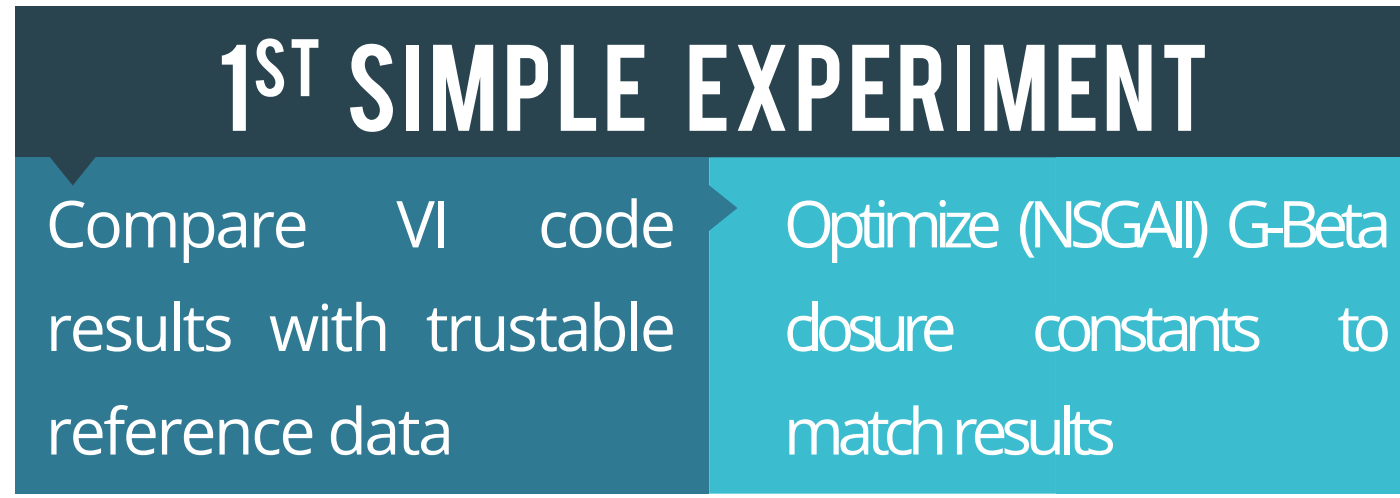
Early experiments show that size of calibration dataset is critical for successful data driven turbulence modelling, motivating multidisciplinary bridges to fill data gaps.



- Instrument**
Pressure Tap, Wake Rake, Load Balance, Particle Image Velocimetry (PIV)
- Instrument**
Ultrasonic Anemometry, Wind LIDAR, SCADA and Turbine Controller Data
- Instrument**
N.A., Direct Numerical Simulation (to provide asymptotic behaviour)
- Instrument**
ADM Aeolus Instrument, Lagrangian Tracers on Optical/IR Measurements
- Instrument**
Hot wire, PIV, Pressure Tap and Stanton Tube

LEARN TURBULENCE MODEL CALIBRATION CURVES

There are many ways to learn from data. Our first experiment consisted in reproducing the way aerodynamicists work [2] with a genetic optimizer. The data pool was too narrow and asymptotic tendencies were unreliable. Our 2nd experiment, a simple version of [4], had a virtually unlimited data pool and used neural networks. Results were better, but computationally expensive. Data assimilation approaches used in EO [7] could yield better results..



PREDICT TURBULENT FLOWS

Once established, the methodology will be applicable to any type of turbulent closure relation, thereby highlighting the common features of seemingly diverse models:



Even when good calibration is achieved, turbulence models will still rely on many coarse assumptions: most popular RANS and LES closures rely on the Boussinesq hypothesis and rule some (if not all) anisotropy out.

INFER NEW CLOSURE TERMS

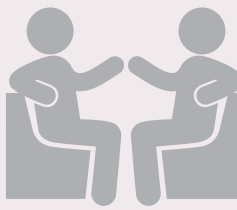
Model calibration curves can hint towards the most problematic simplifications behind current turbulence models [5], and neural networks can even learn improved closure terms [4]. But learning algorithms do not aim to replace researchers: like genetic airfoil optimizers enhance the work of airfoil designers, neural networks can empower turbulence modellers.

- [1] A first course in Turbulence, Tennekes & Lumley MIT Press
- [2] Modification of the boundary layer calculation in Rfoil for improved airfoil stall prediction van Rooij R, TU-Delft Report IW-96087R
- [3] An evaluation of RANS turbulence modelling for aerodynamic applications, Catalano P & Annato M, Aerospace Science and Technology, 7 493-509
- [4] Machine Learning Methods for Data-Driven Turbulence Modeling, Zhang ZJ & Duraisamy K, AIAA 2015-2460
- [5] A paradigm for data-driven predictive modeling using field inversion and machine learning, Parish EJ & Duraisamy K, J. Comp. Phys. 305 758-774
- [6] La turbulence par l'image, Heas P, Heitz D and Memin E La Recherche: L'Actualité des Sciences 2010-444
- [7] Parameterization of Turbulence Models Using 3DVAR Data Assimilation, Olbert AJ, Nash S, Rognoli E and Harrett M, 11th International Conference on Hydrometeorology

Tune the G-Beta constants of a viscous-inviscid (VI) solver (RFOIL) with genetic algorithms (NSGA2).

Process CFD Fields to learn neural VI closure relations.

Gather partners to share data and write proposals. Summer schools: JMBC Turb, LxMLS16 and 8th ESA EO.



Group D8 of the AE-2223 course developed the neural network code: Koopman, Henger, Lebesque, Mekic, Mollinga, Vijverberg, Reutelingersperger

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