# Understanding and controlling fluid flows using data, physics, and machine learning

**Scott Dawson**

Mechanical, Materials and Aerospace
Engineering Department
Illinois Institute of Technology

**ATPESC Dinner Talk**
**August 3, 2023**

ARGONNE
ATPESC2023
EXTREME-SCALE COMPUTING

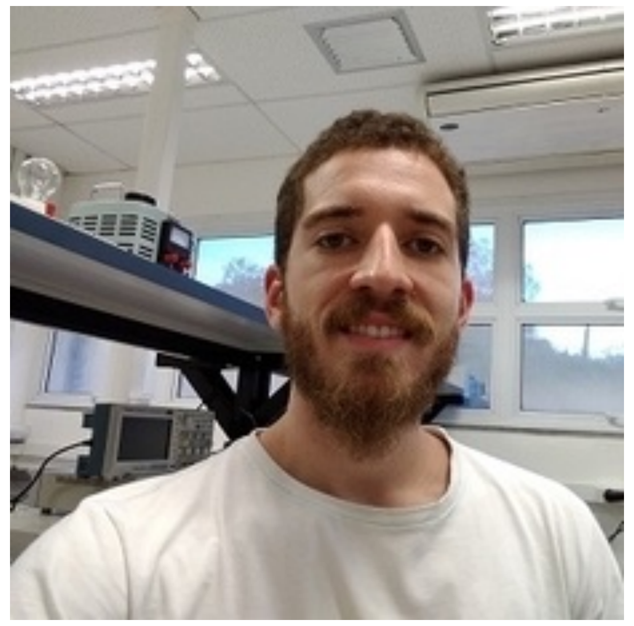
ILLINOIS INSTITUTE
OF TECHNOLOGY
Armour College of Engineering

# Collaborators and contributors


Katherine Asztalos


Abdulrahman Almashjary


Barbara Lopez-Doriga


Tarcísio Deda


Jane Bae

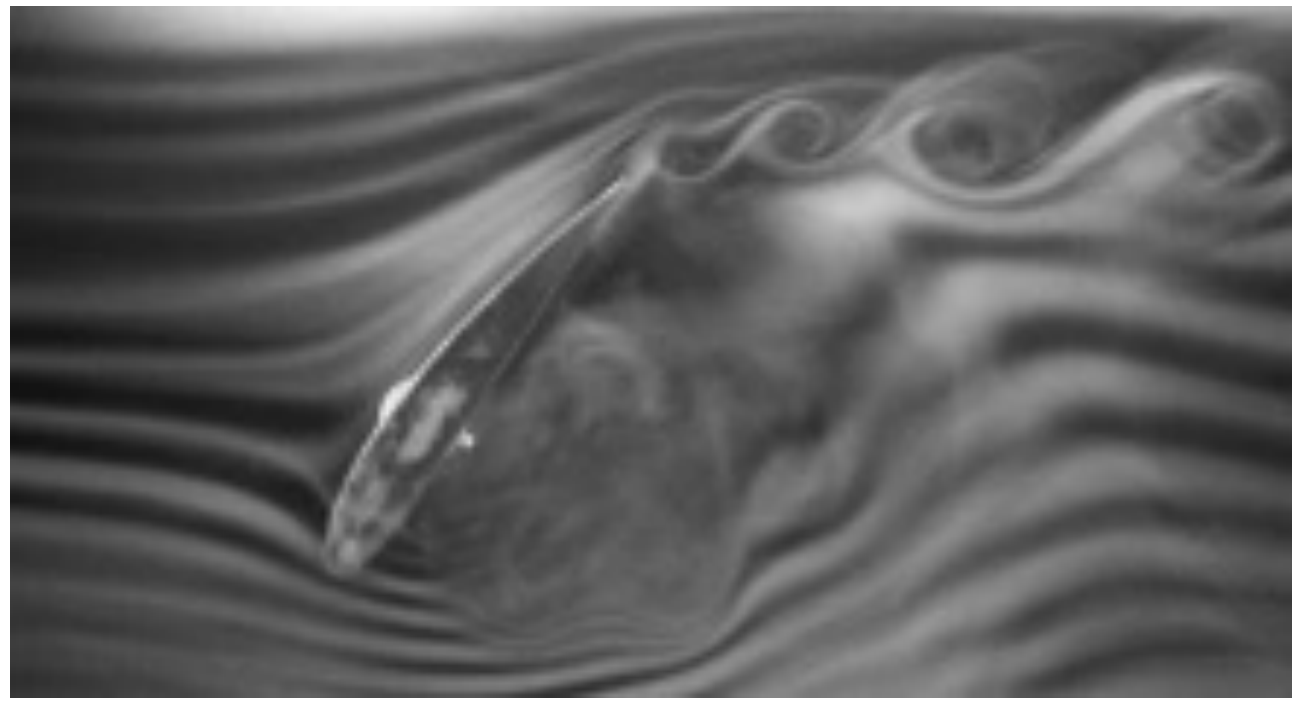

Eric Ballouz


William Wolf

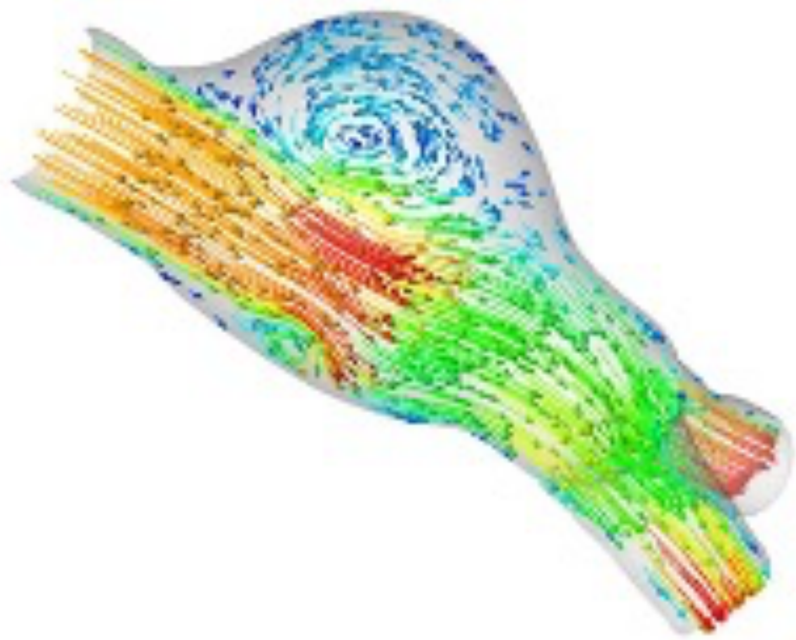
# About me


Illinois Tech
2019-
Princeton (grad school)
2011-2016
Caltech (postdoc)
2016-2018
Melbourne, Australia
until 2011

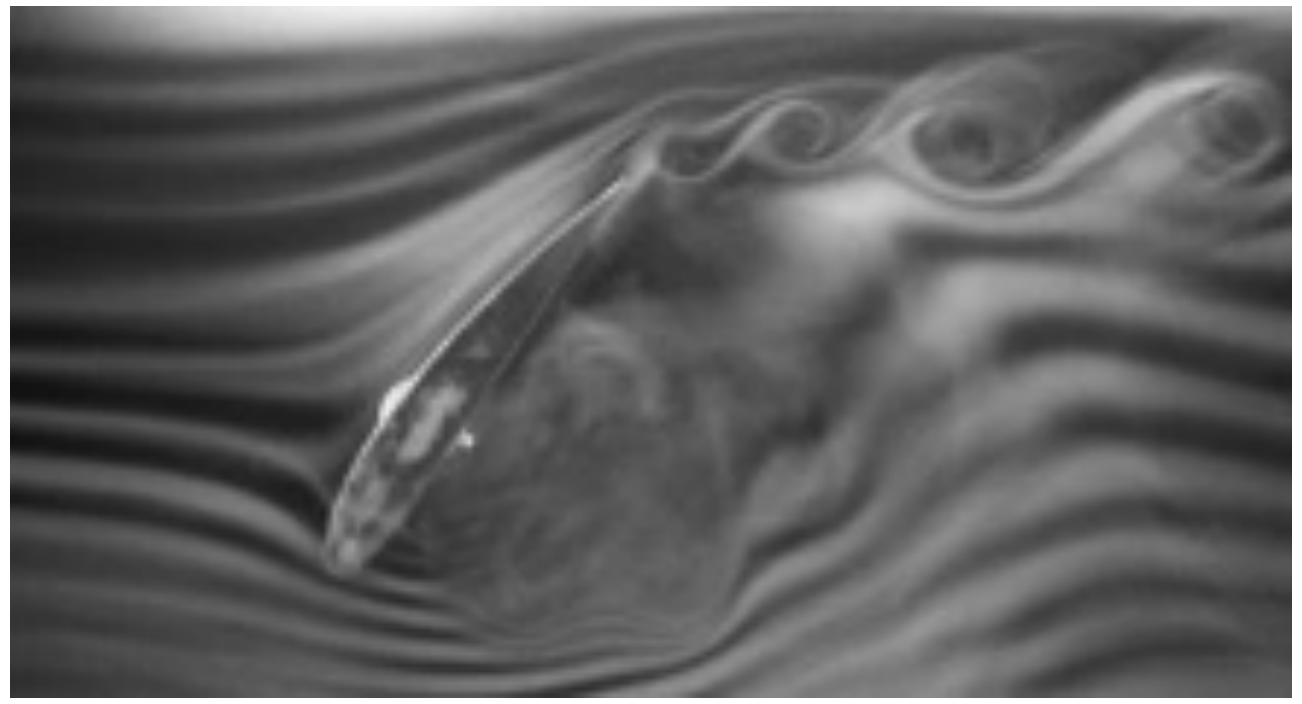
# Turbulent fluid flow is ubiquitous across a broad range of applications



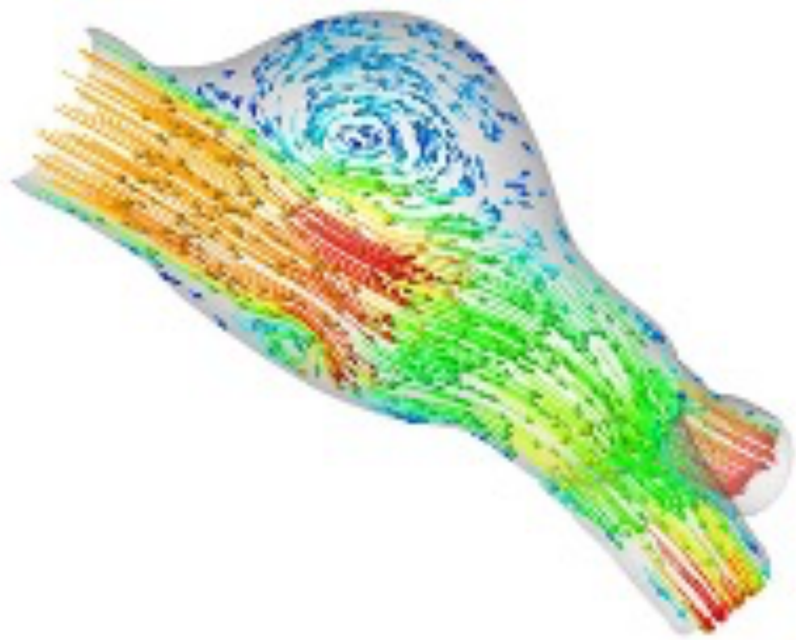


# Turbulent fluid flow is ubiquitous across a broad range of applications



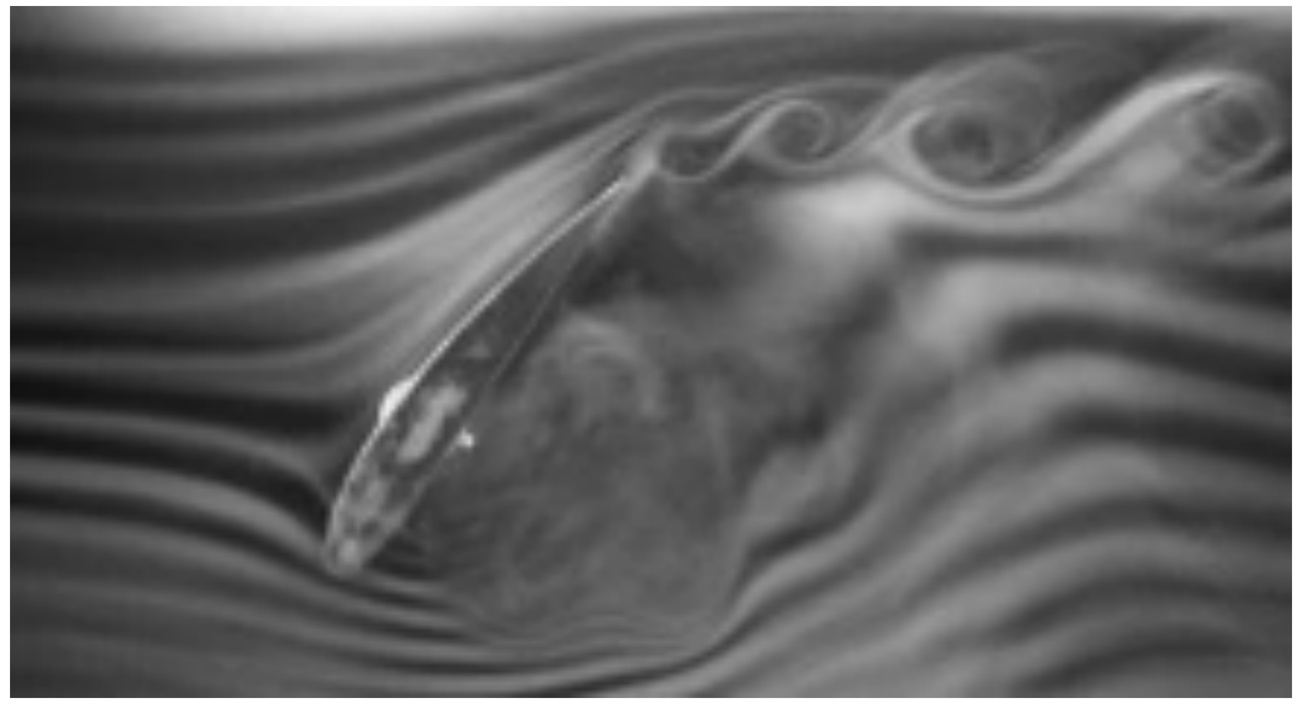


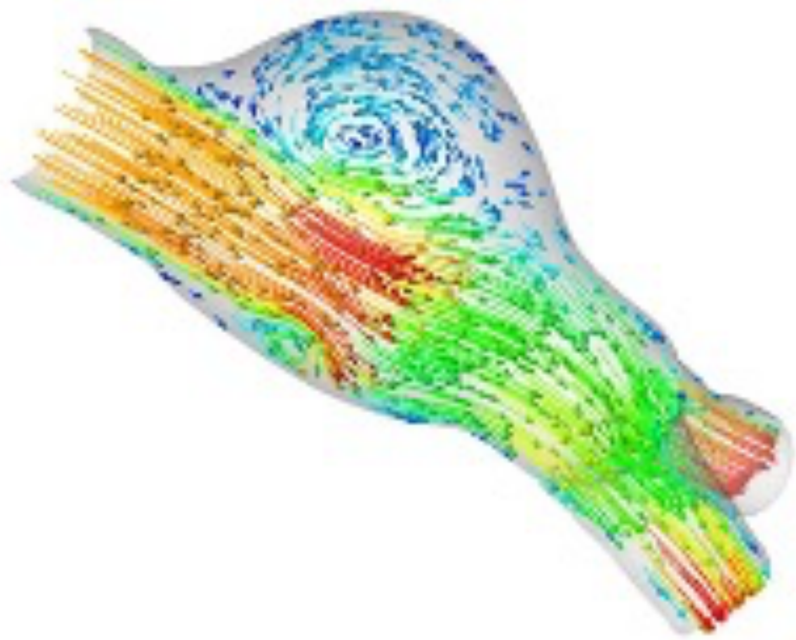
**Turbulence is important:**

- 50% of drag on a commercial aircraft is due to turbulence in the boundary layer on its surface [Marusic et al., 2010]
- About 10% of all the electricity generated every year is currently consumed in the process of overcoming the effects of turbulence.

# Turbulent fluid flow is ubiquitous across a broad range of applications



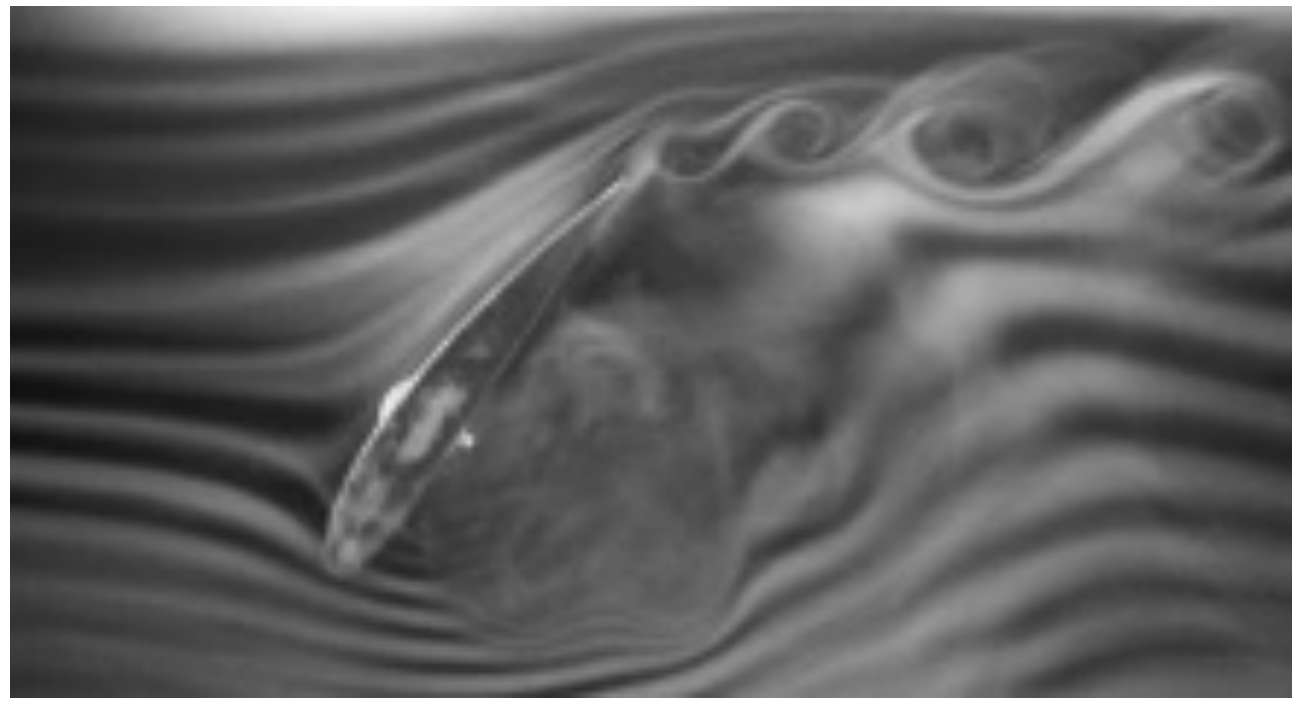


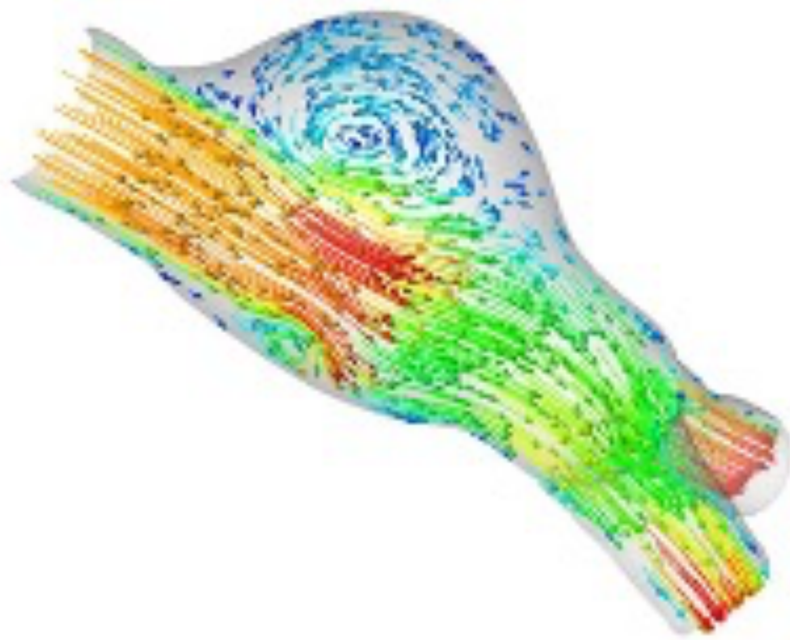
**Turbulence is conceptually hard:**

- "When I meet God, I am going to ask him two questions: Why relativity? And why turbulence? I really believe he will have an answer for the first" - Werner Heisenberg
- "Turbulence is the last great unsolved problem of classical physics" - (likely at least) one of Albert Einstein, Richard Feynman, or Arnold Sommerfeld

# Turbulent fluid flow is ubiquitous across a broad range of applications





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We are still very far from being able to numerically solve the PDEs (Navier-Stokes equations) for most of these examples

# Turbulent fluid flow is ubiquitous across a broad range of applications

**Turbulence is computationally hard:**
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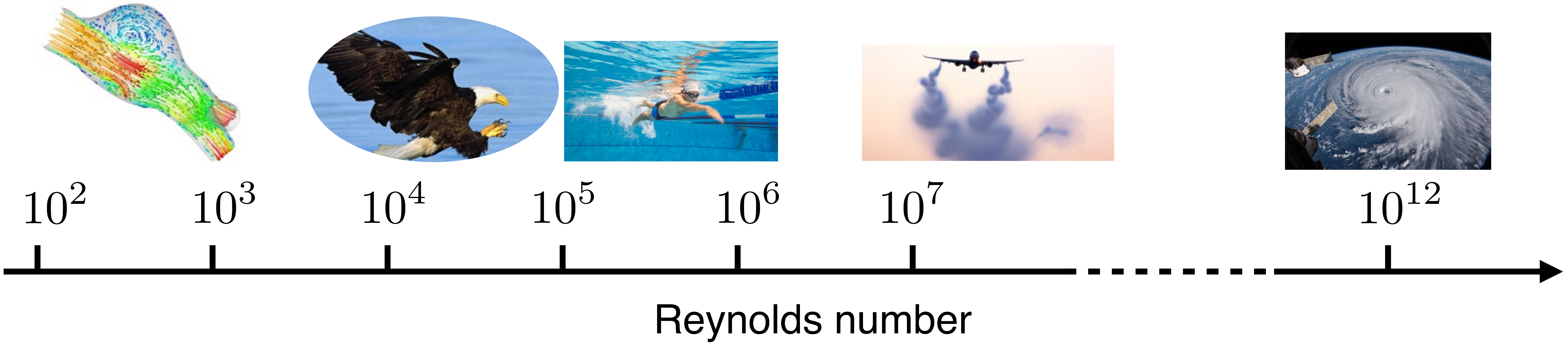
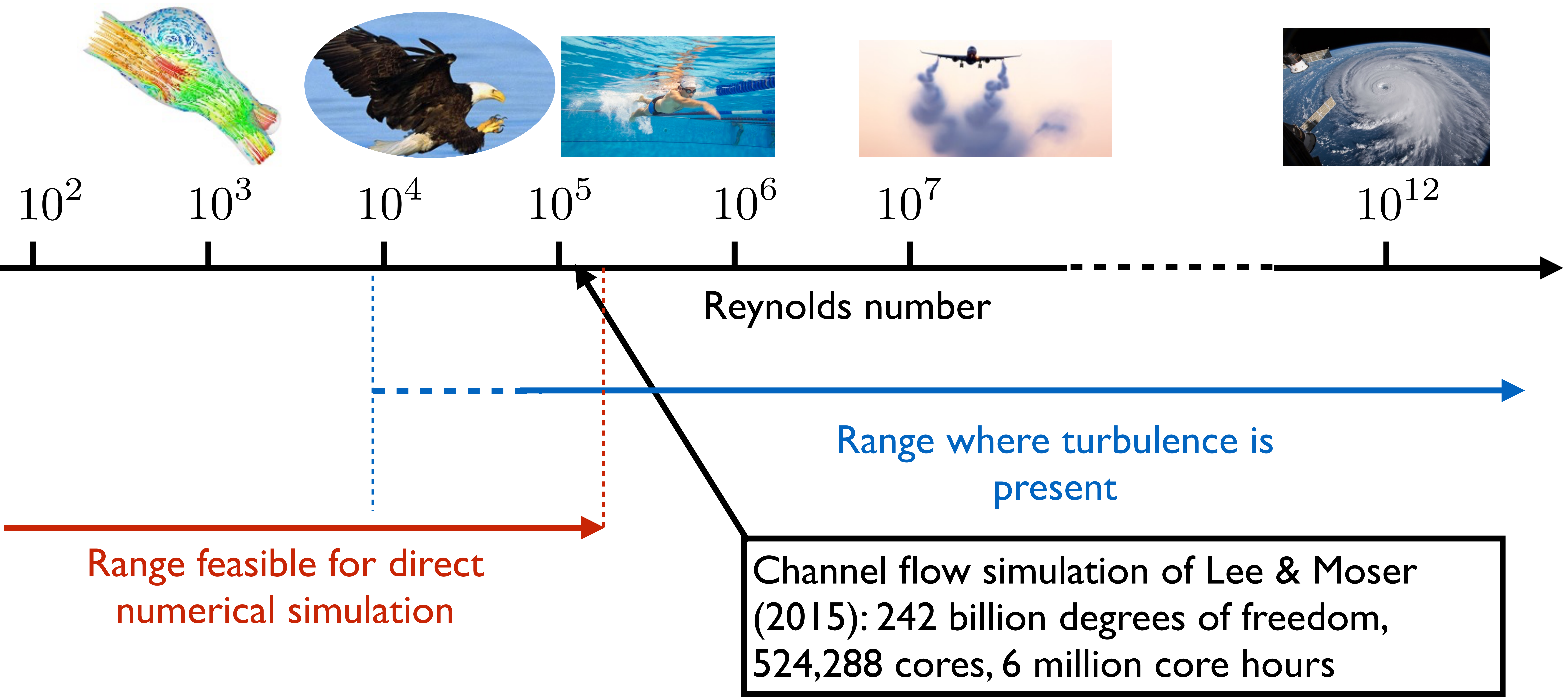
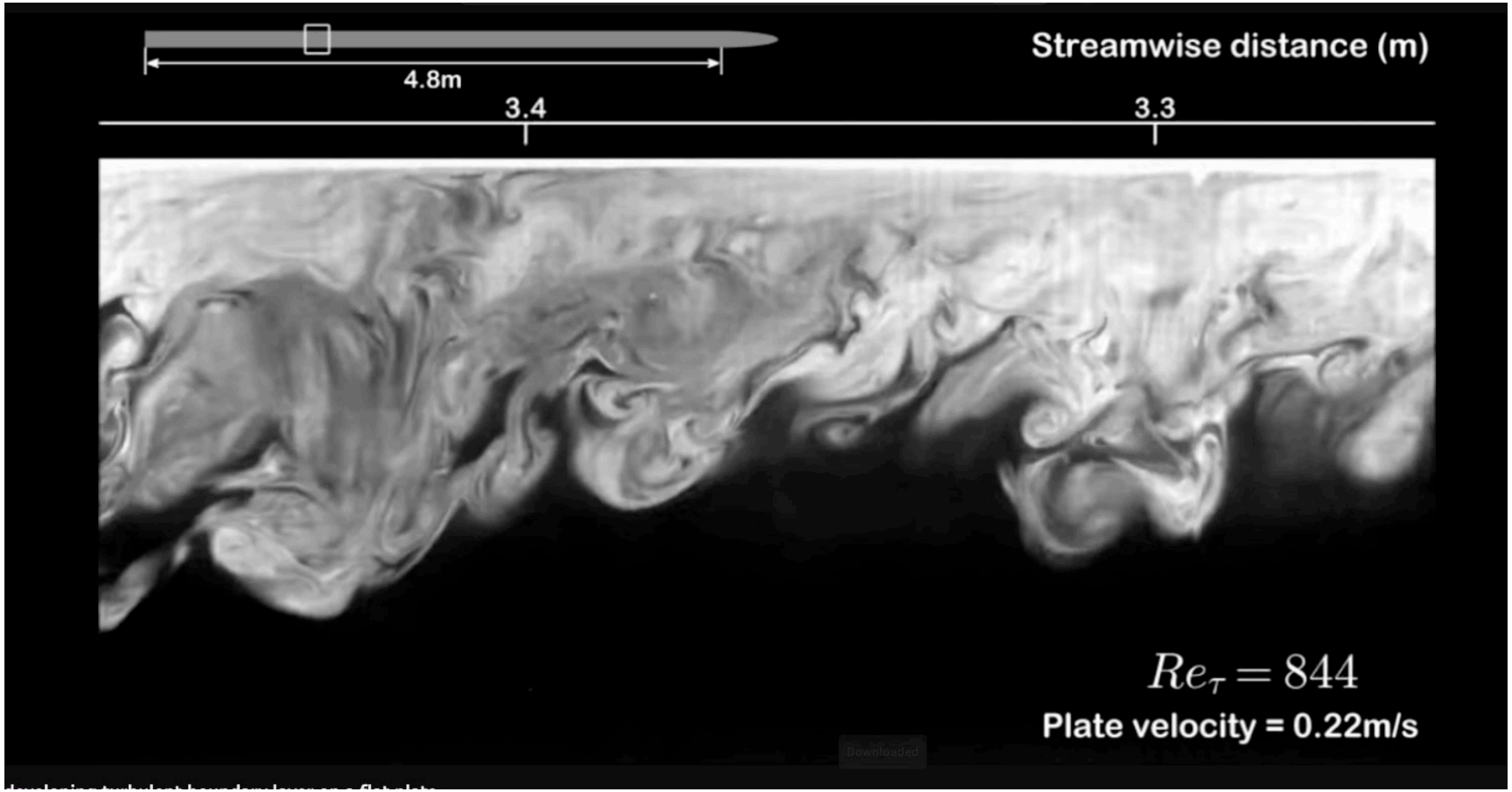
Fluid flows that are fast and/or large can have a very large range of length and time scales that must be resolved (quantified by the Reynolds number)



# Turbulence is computationally expensive to simulate accurately



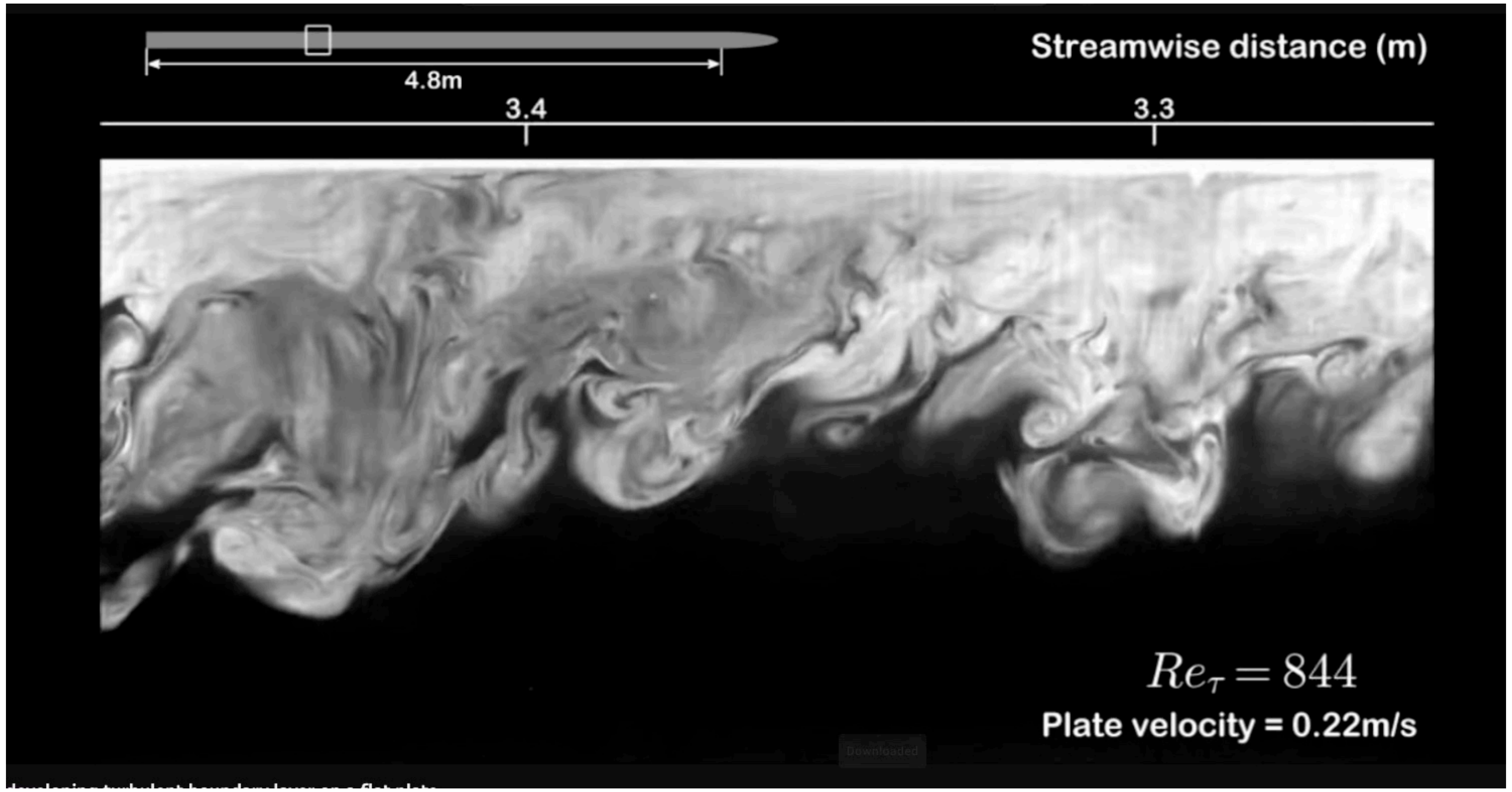
# Turbulence has structure




[Lee et al. 2012]

- How can such structure be understood? Predicted? Controlled?

# How can we decompose turbulence to isolate coherent structures?

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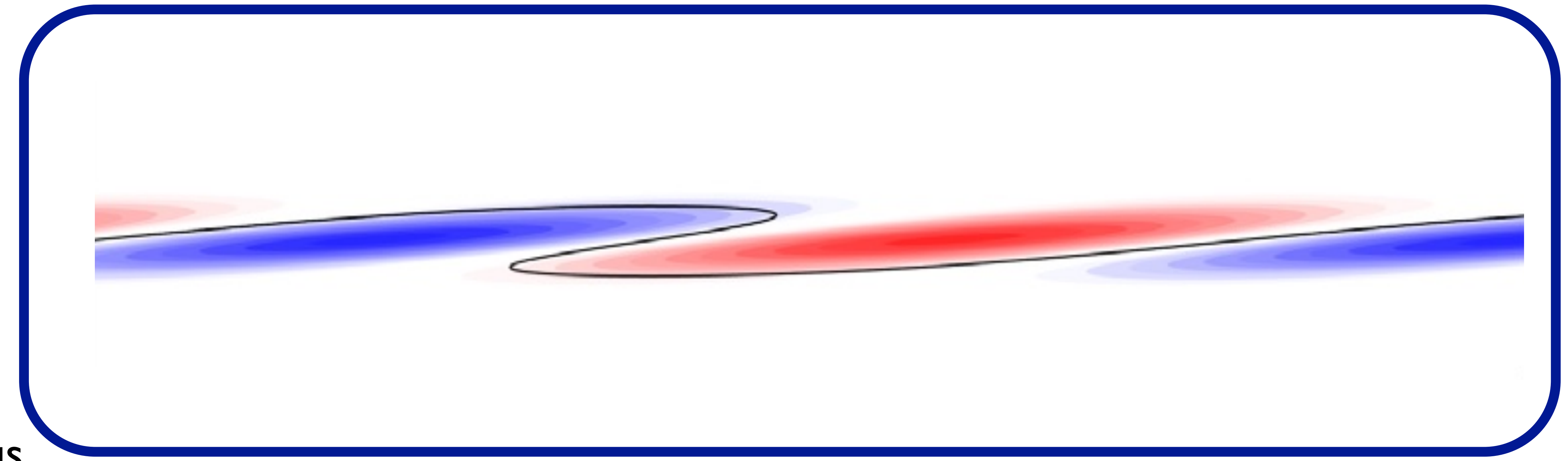
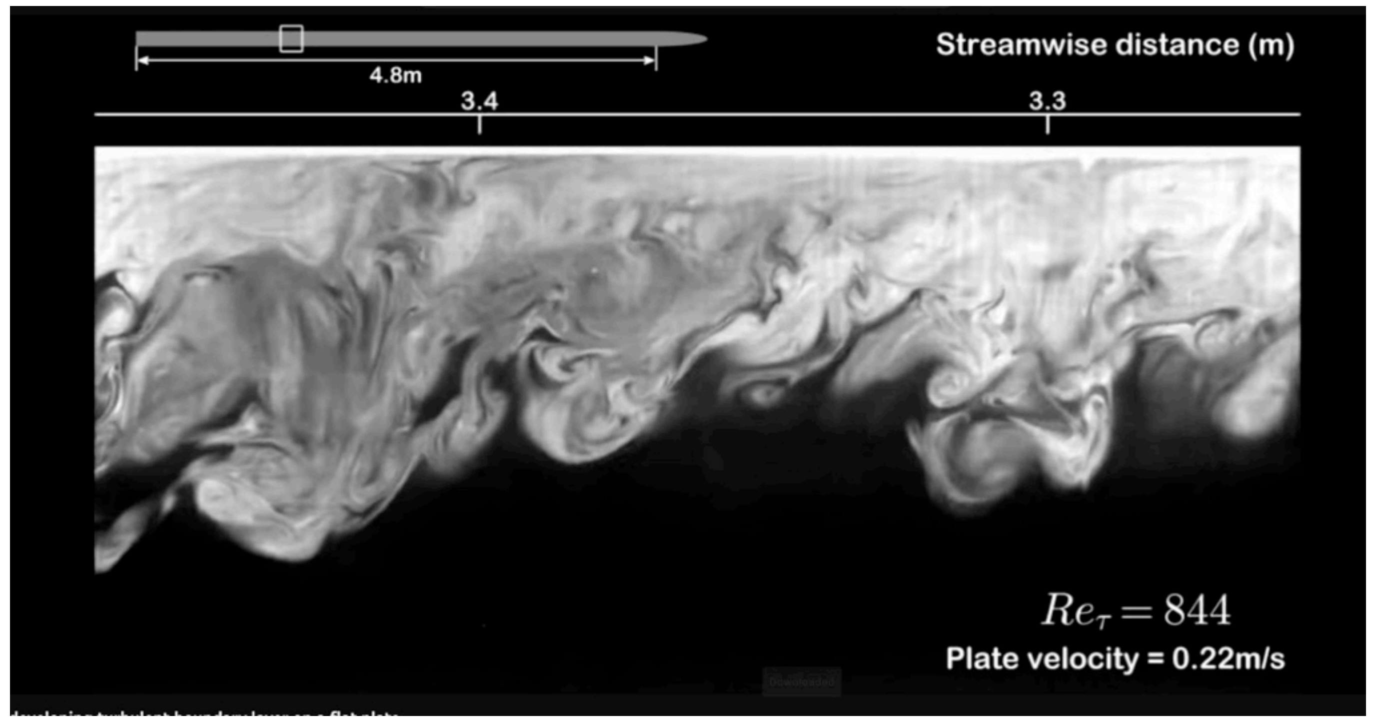


Structures at various length- and time-scales

# How can we decompose turbulence to isolate coherent structures?

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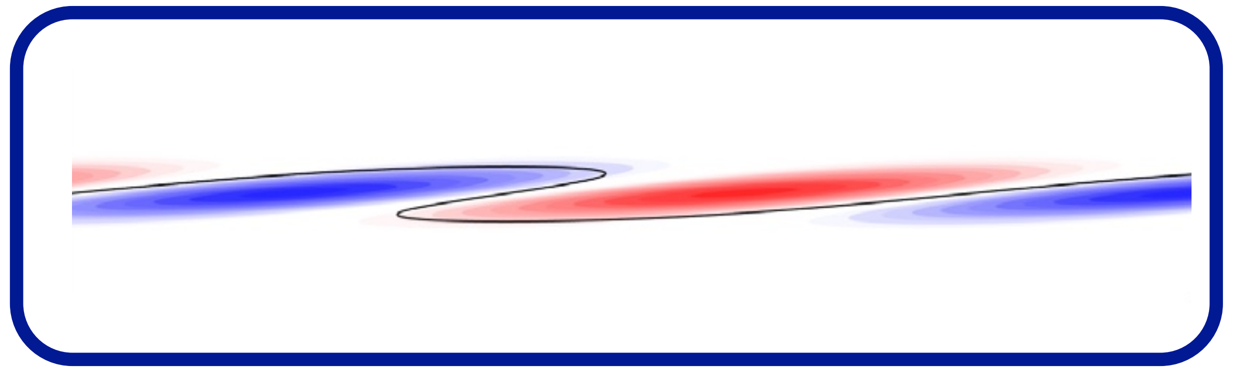
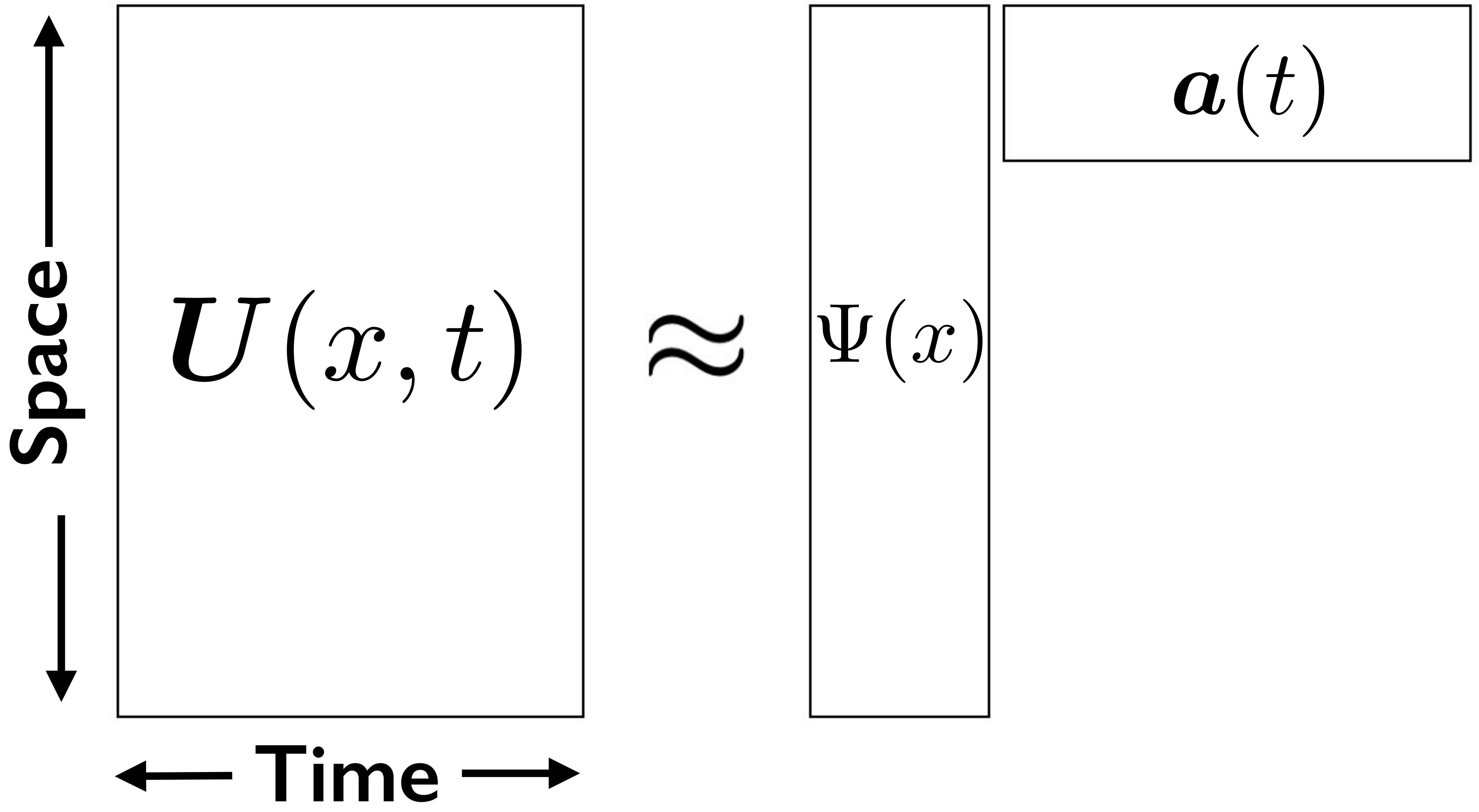
$\sum$ 

- We look to decompose a spatio-temporal field into a sum of spatial modes with time-varying coefficients:

$$\boldsymbol{u}(x,t) = \sum_{j=1}^{m} \psi_j(x) a_j(t)$$

- For discrete coordinates in space and time:

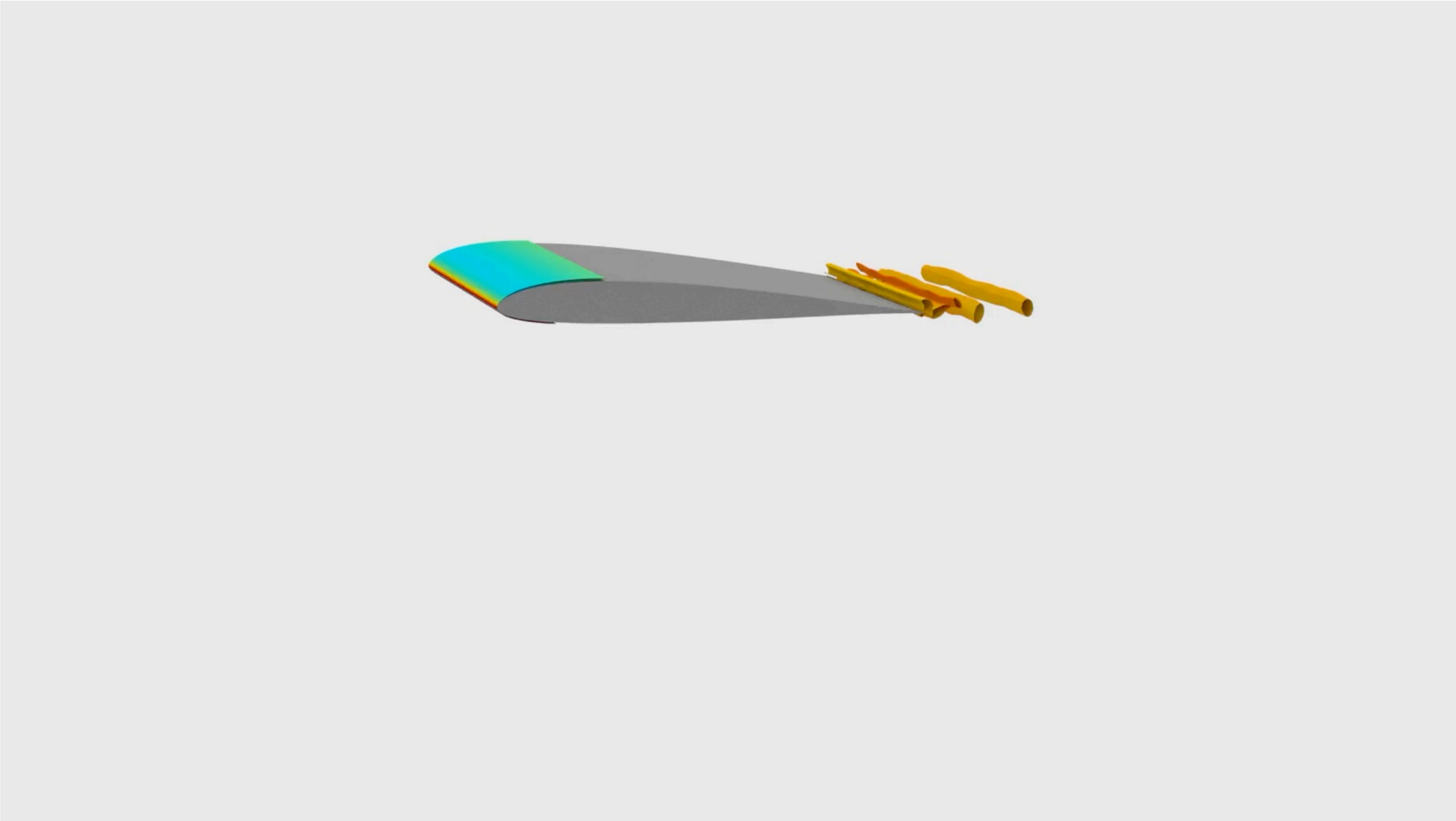


# Most of my research

# Extending space-time decompositions to non-stationary flows

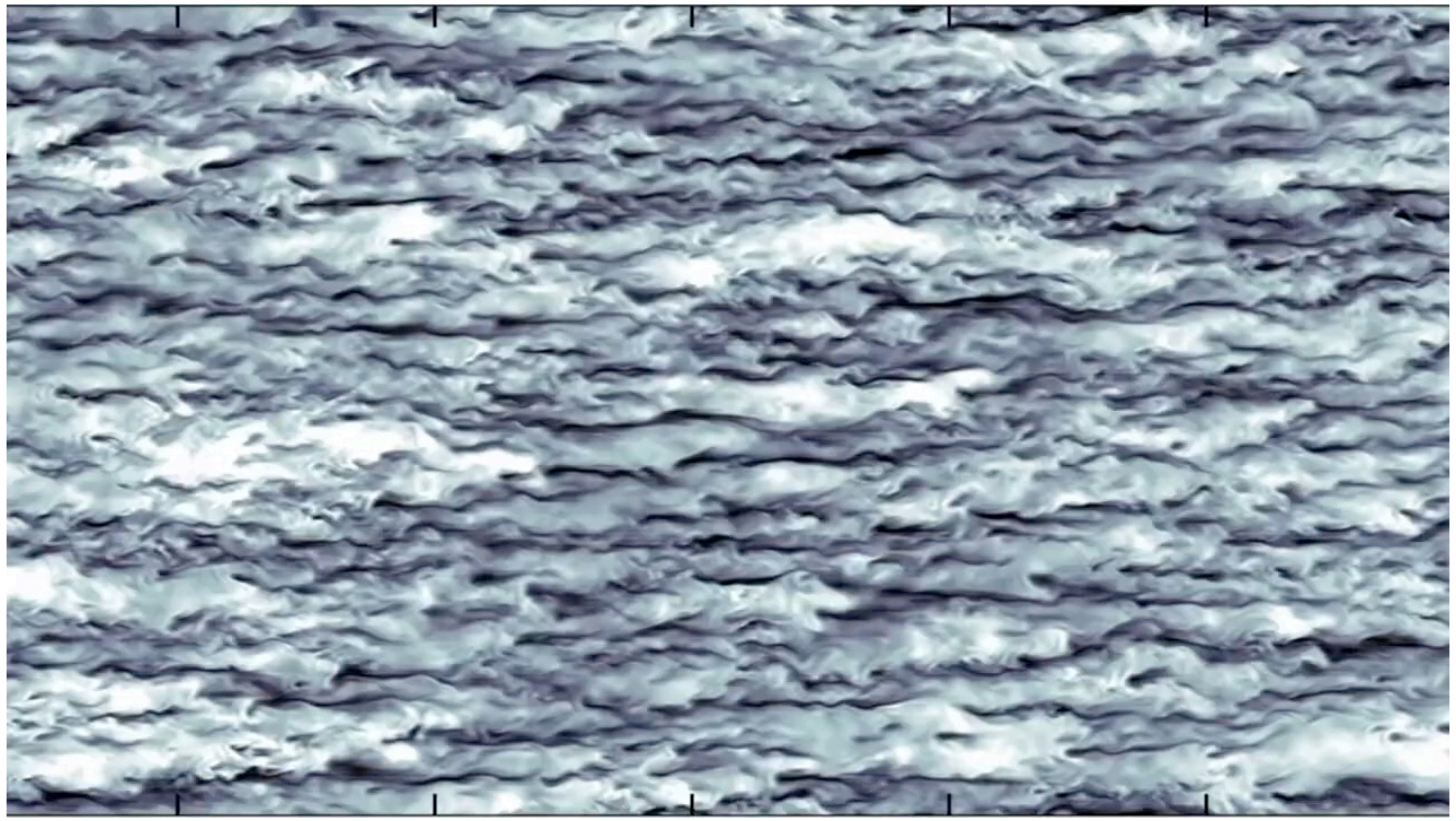
There are many methods of analysis that are designed for fluid flows that are *statistically stationary*

Deep dynamic stall



Ramos et al., PRF 2019 (video: https://youtu.be/2KcK1rBQb0Y)

Non-equilibrium boundary layer



Lozano-Durán et al., JFM 2019

We look to extend such methods to a broader class of flows
(though I won't discuss this project tonight)

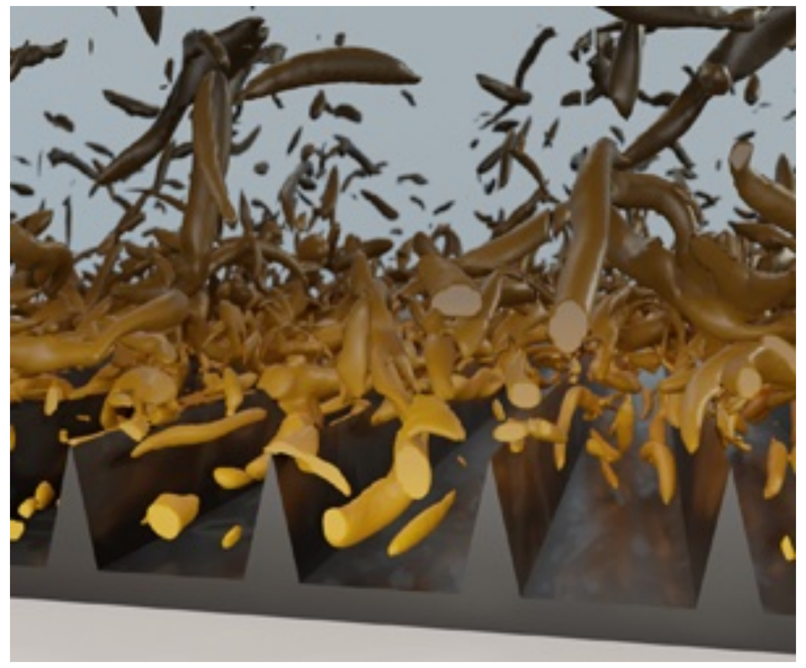
# How can we control unsteady and turbulent flows?

Reducing, eliminating, or otherwise manipulating turbulence and unsteadiness in fluid flows can lead to improvements in efficiency and performance across a broad range of applications

- **Passive control:** modify surface geometry or properties (e.g. grooves, riblets) to manipulate the near-wall turbulence
- **(Re)active control:** Add energy/momentum into the flow in a targeted manner, possibly informed by real-time measurements

**Riblets Reduce Drag, Emissions On Swiss Flight**

Graham Warwick October 14, 2022

[Endrikat et al., 2022]

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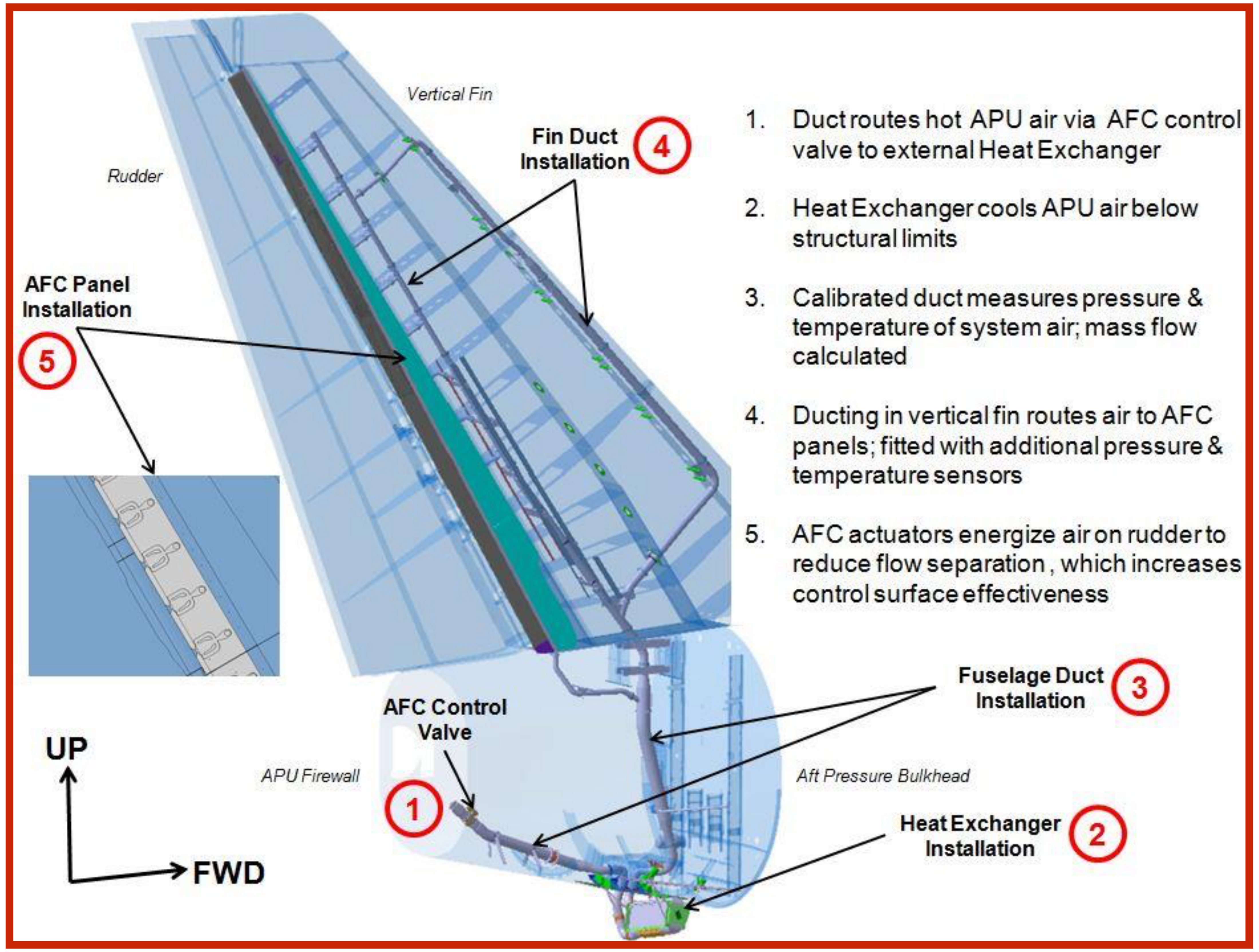


[Vijgen et al., 2016]

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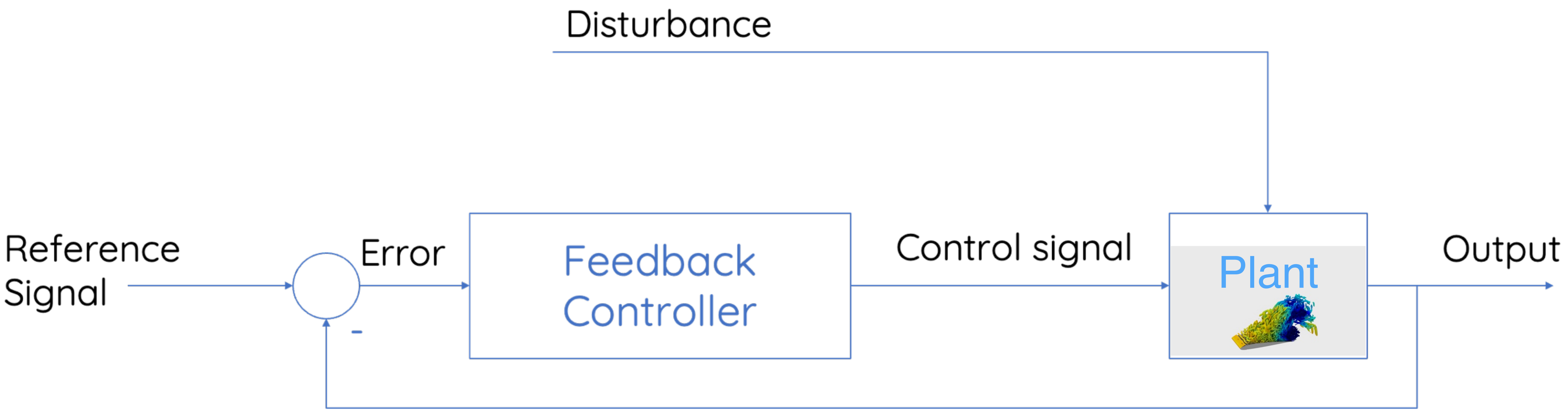


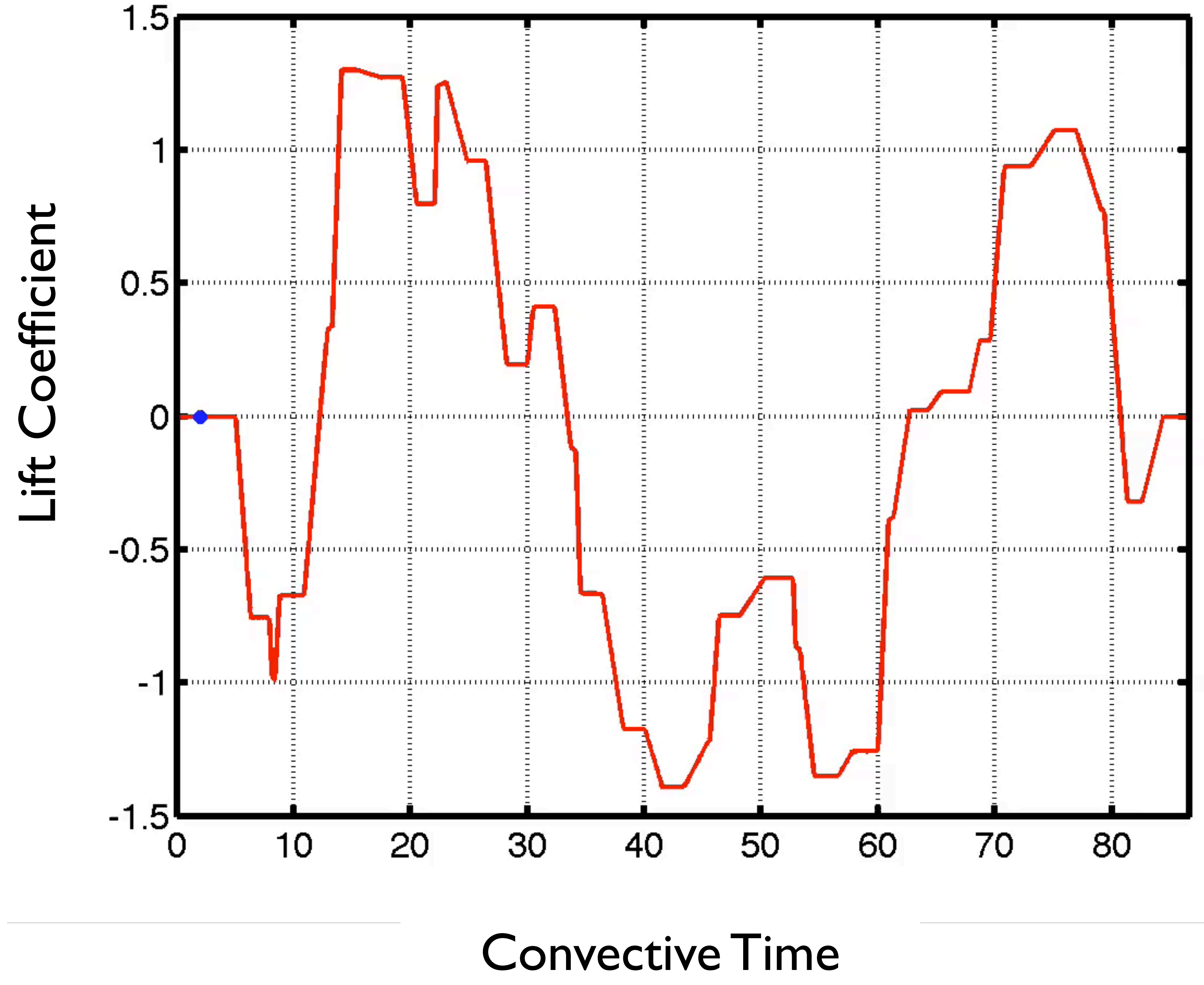

- How should we design the **controller**?

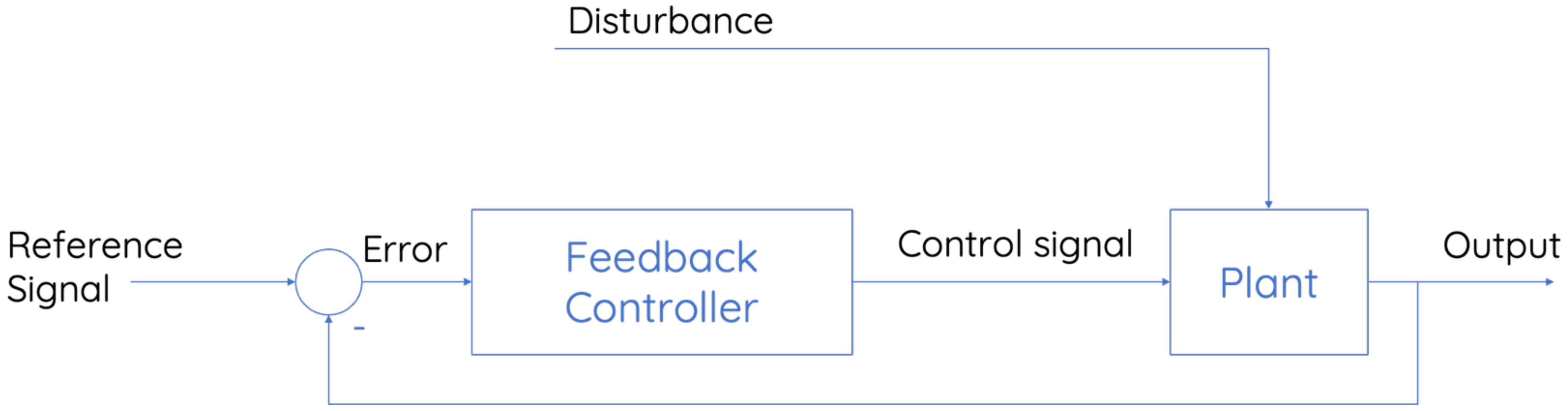
- **If** we can model the plant as a **linear dynamical system**, then then we have many tools and theory at our disposal

# How can we control unsteady and turbulent flows?

- **If** we can model the plant as a **linear dynamical system**, then then we have many tools and theory at our disposal

Lift tracking control for a 2D flat plate, Re = 100

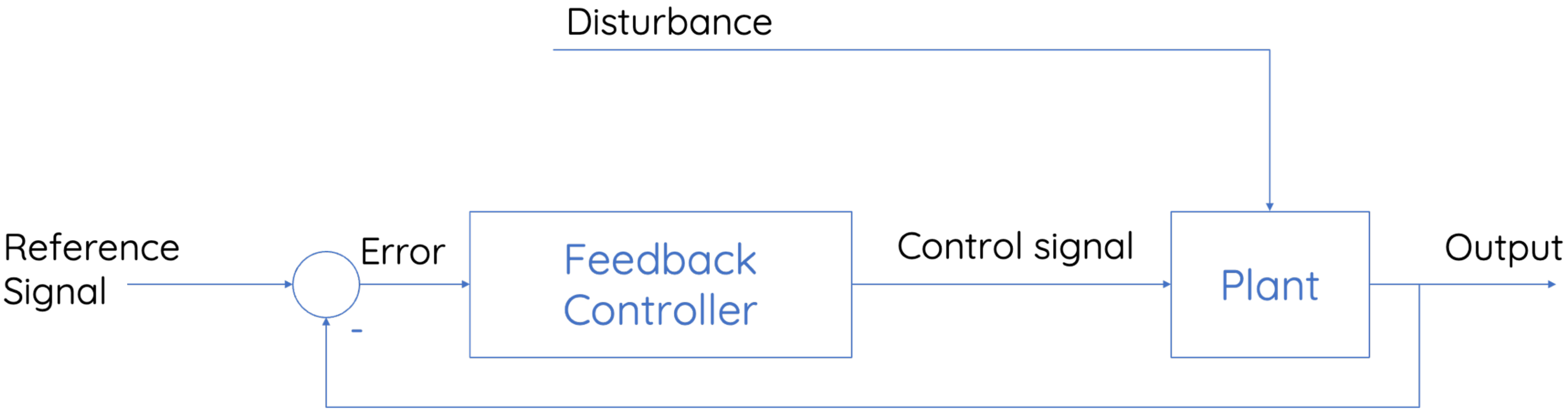



Stabilization of an "inverted pendulum airfoil"

# How can we control unsteady and turbulent flows?

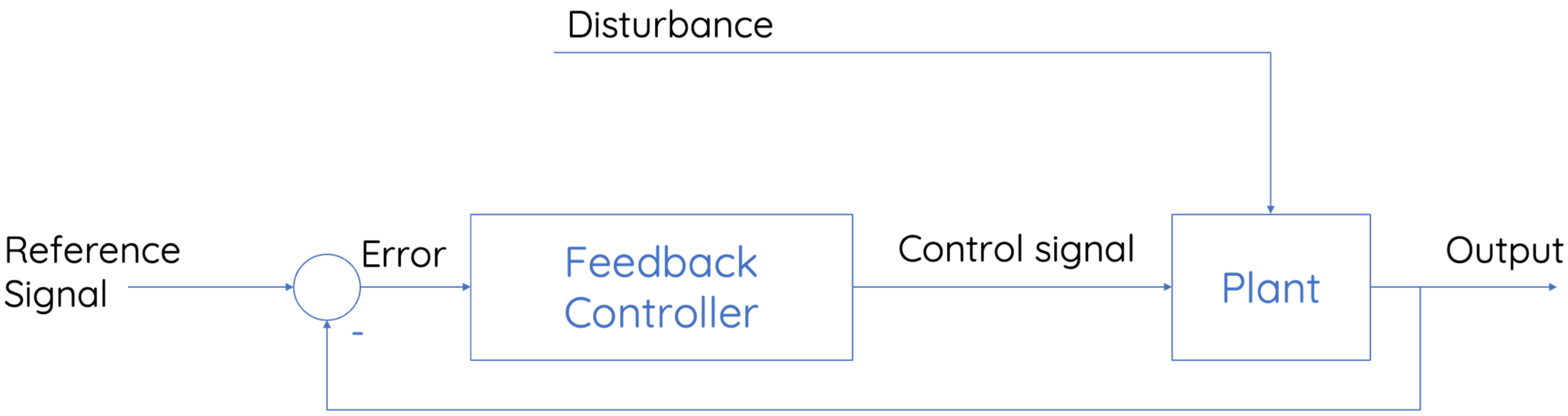
- **If** we can model the plant as a **linear dynamical system**, then then we have many tools and theory at our disposal




- **Issue:** Most interesting fluid flows are **highly nonlinear**, and evolve very far away from (sometimes unknown) equilibrium points

# How can we control unsteady and turbulent flows?

- **Issue:** Most interesting fluid flows are **highly nonlinear**, and evolve very far away from (sometimes unknown) equilibrium points

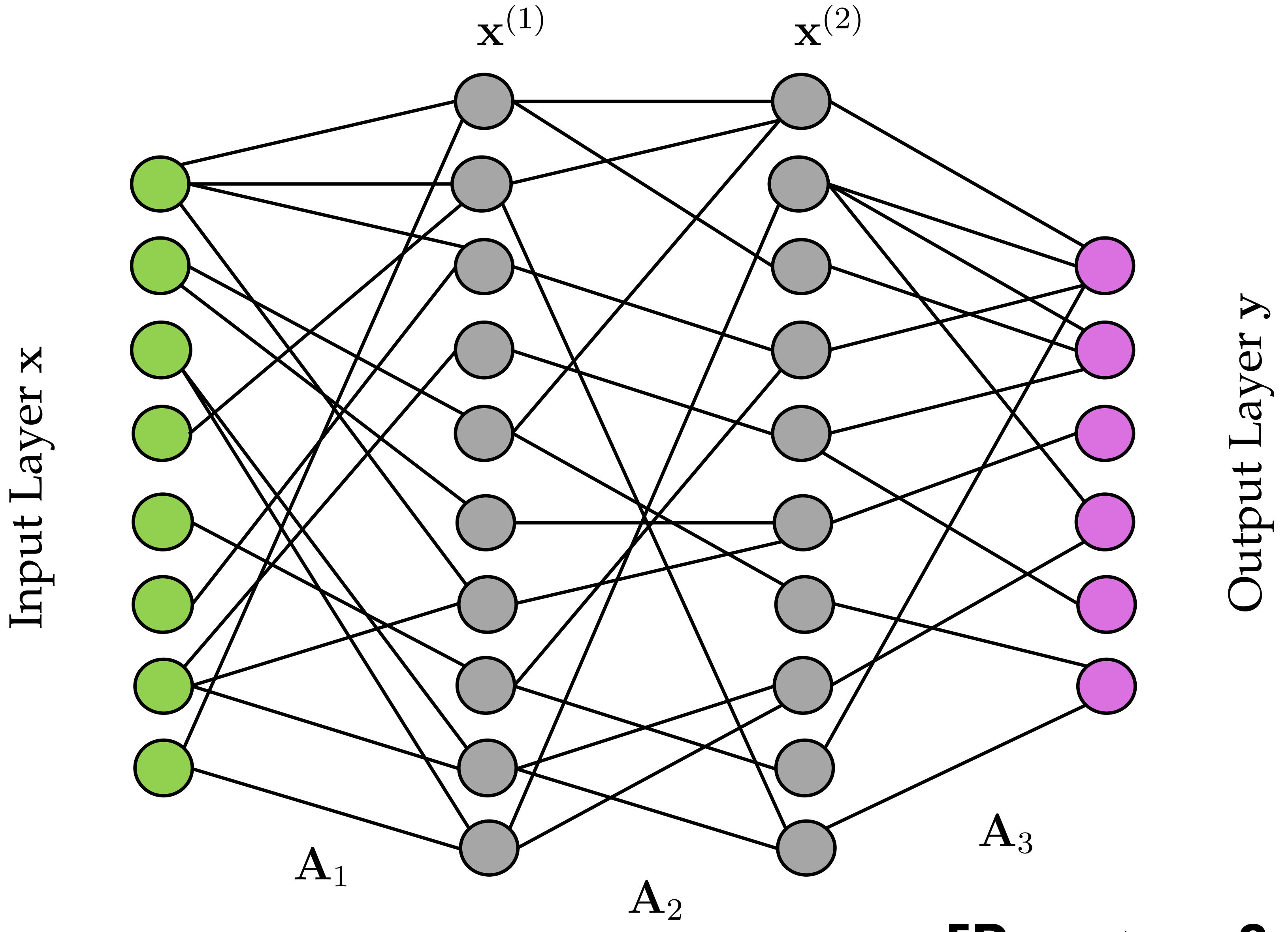



- To control a nonlinear system, we wish to model the plant and controller using **nonlinear functions**

- **Neural networks** provide a convenient means of modeling such functions

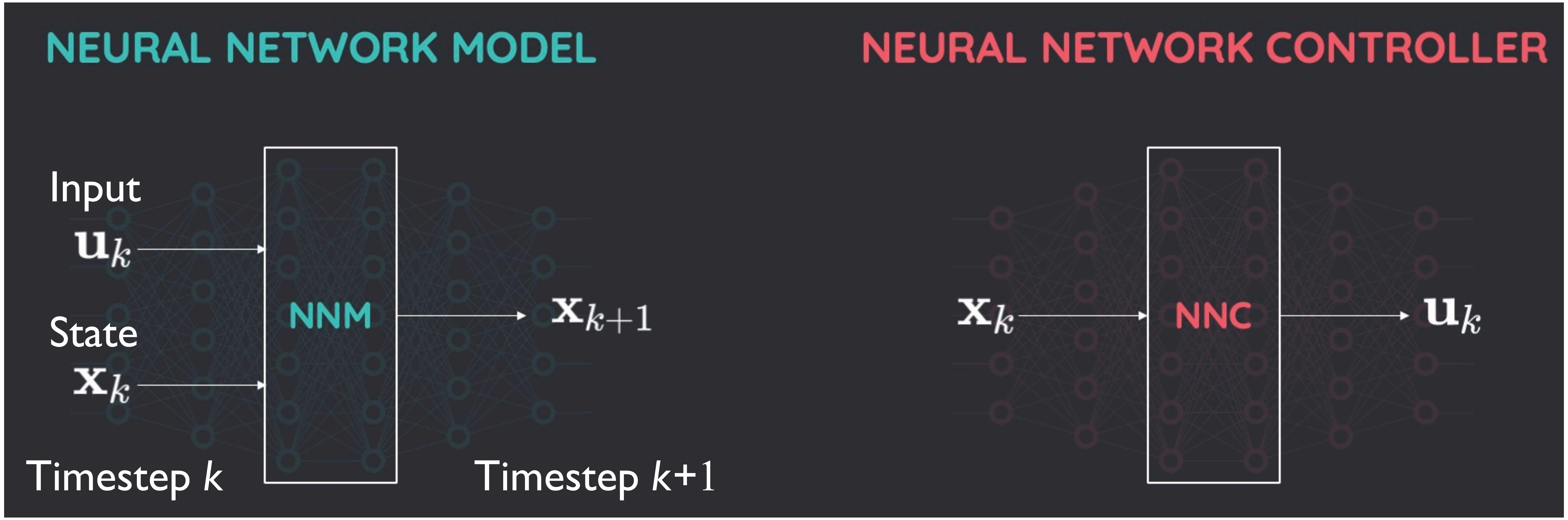
# Neural networks

- **Neural networks** give a means of representing arbitrary, complex functions through the composition and addition of many simple functions
- Subject to certain conditions, it can be shown that ANY function can be approximated by neural networks, to arbitrary accuracy




[Brunton & Kutz, 2020]

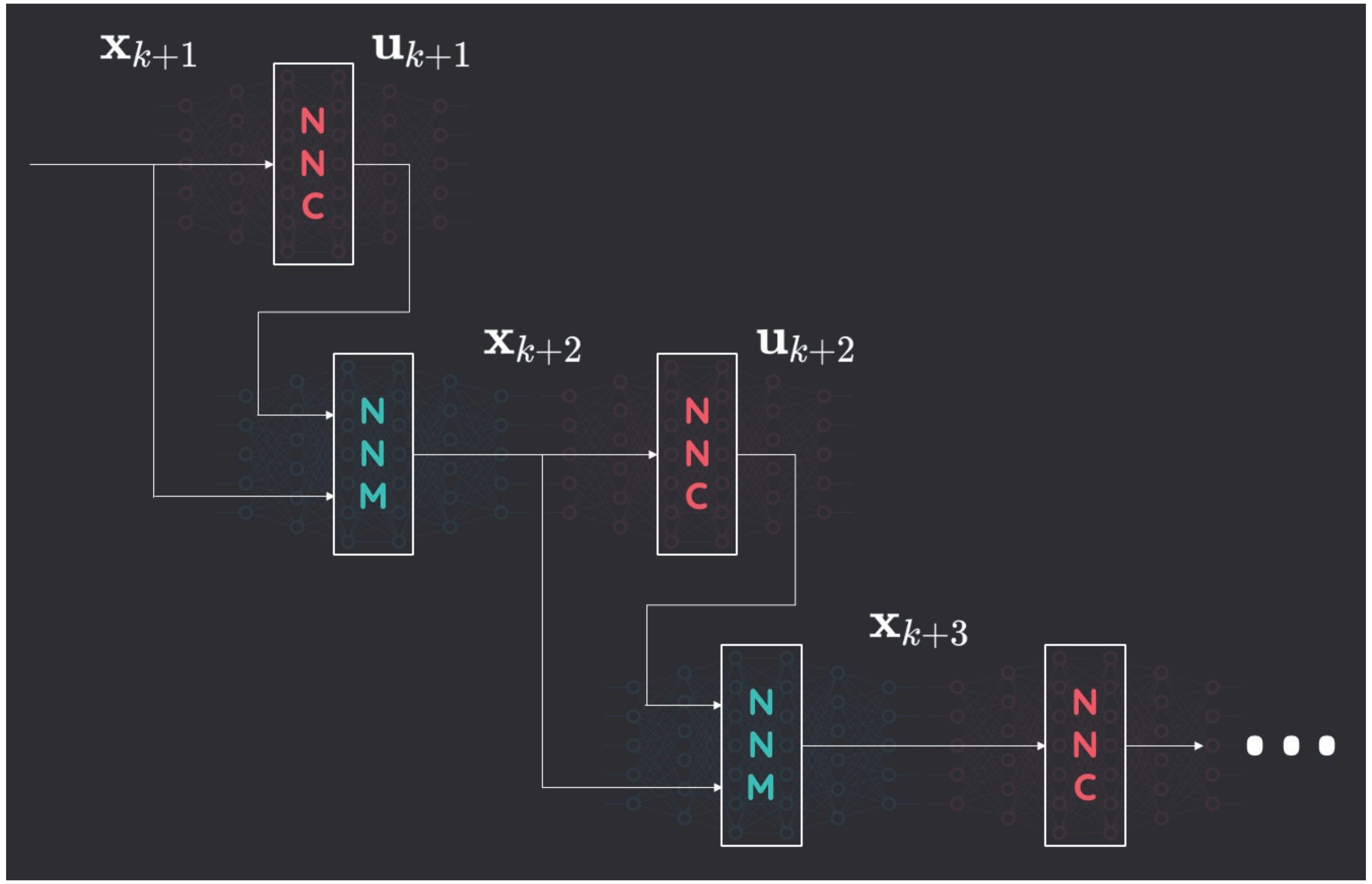
# Neural networks for flow control




- The **neural network model** predicts future states based on the current ones and on the control input
- The **neural network controller** provides a control input based on real-time measurements

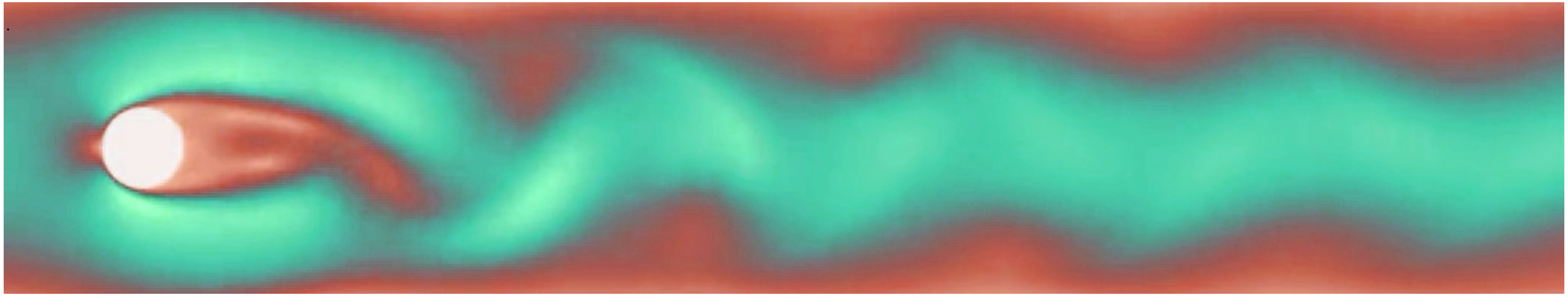
# Neural networks for flow control

- We develop a methodology to simultaneously train:
  - A surrogate neural network model for the fluid flow (NNM)
  - A neural network for the controller (NNC)
- The controller attempts to suppress all unsteadiness in the flow
- The coupled neural networks have a recurrent structure



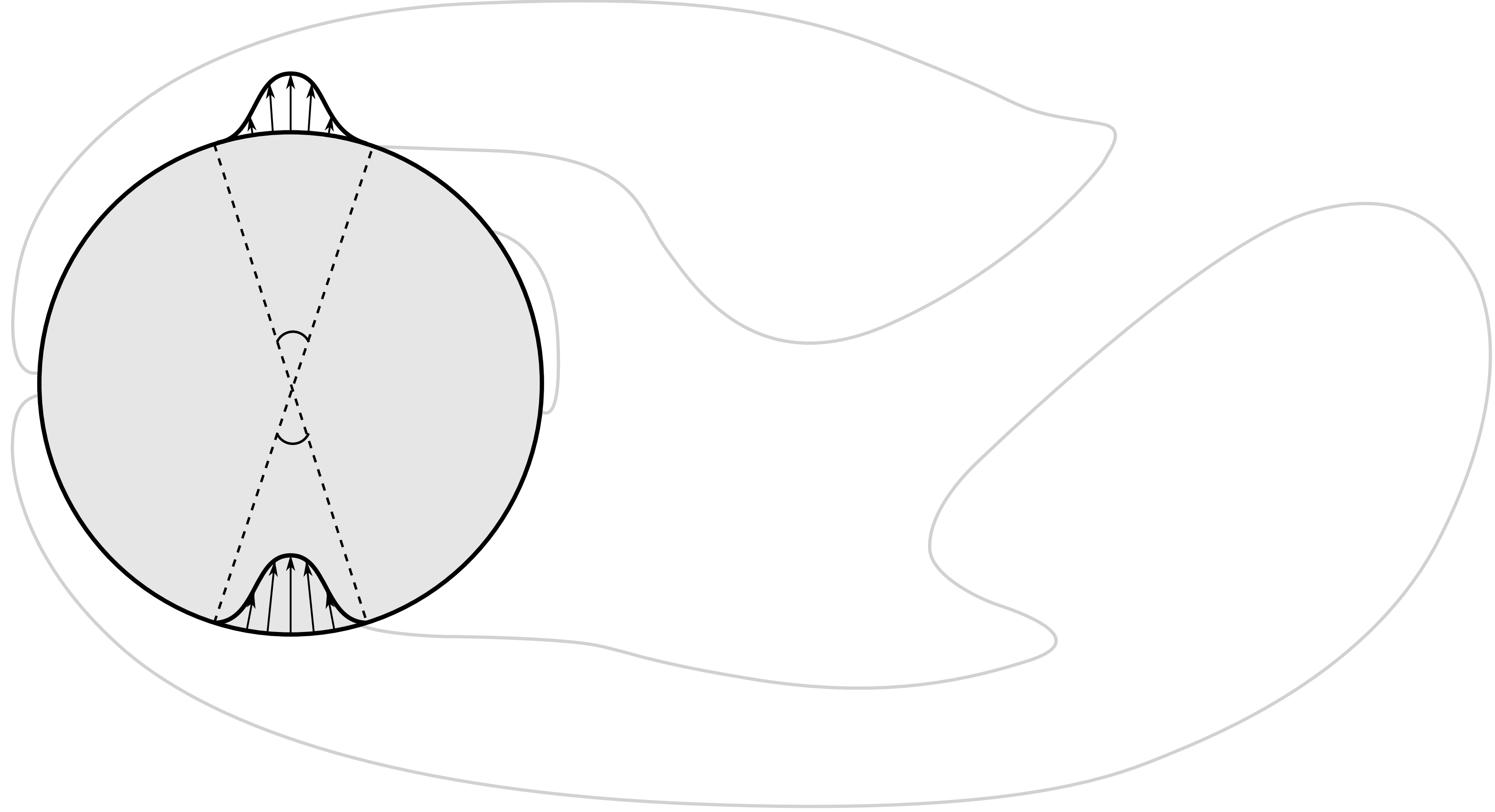
# Stabilization of flow over a circular cylinder

- Flow over a circular cylinder exhibits periodic vortex shedding in its wake
- We will attempt to suppress this vortex shedding



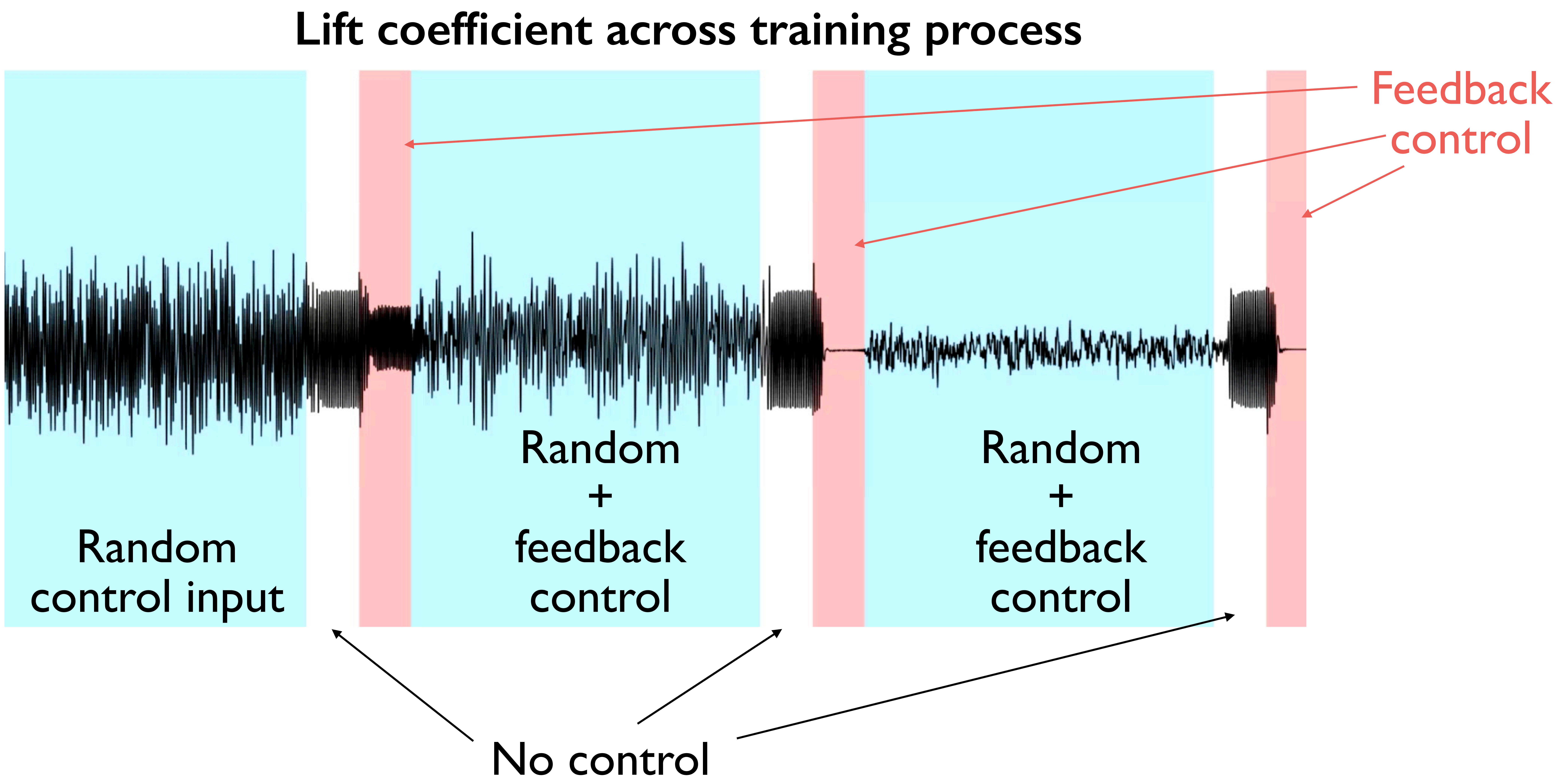
**Confined cylinder flow at a Reynolds number of 150**

- Control input is localized blowing/suction at the top and bottom of the cylinder



- Configuration matches that used in previous control studies [Rabault et al., 2019]

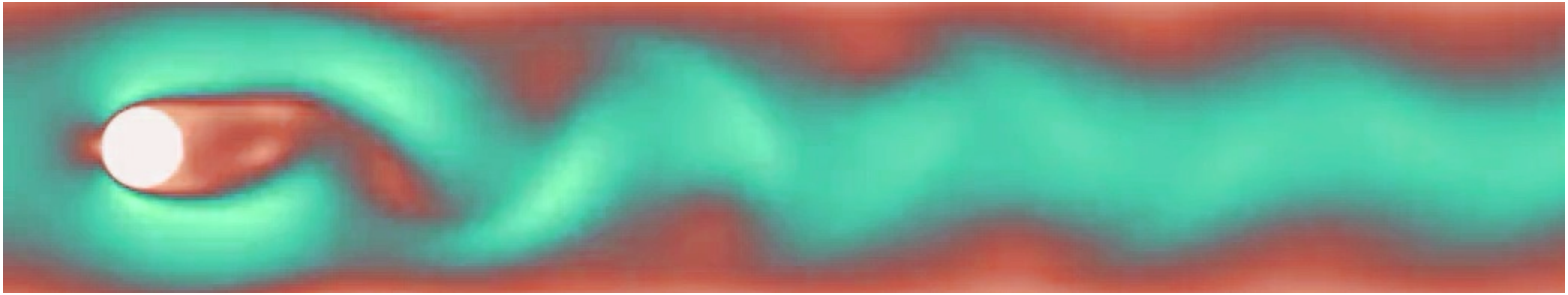
# Stabilization of flow over a circular cylinder




*Iterative training process generates increasingly more data near the desired equilibrium fixed point*

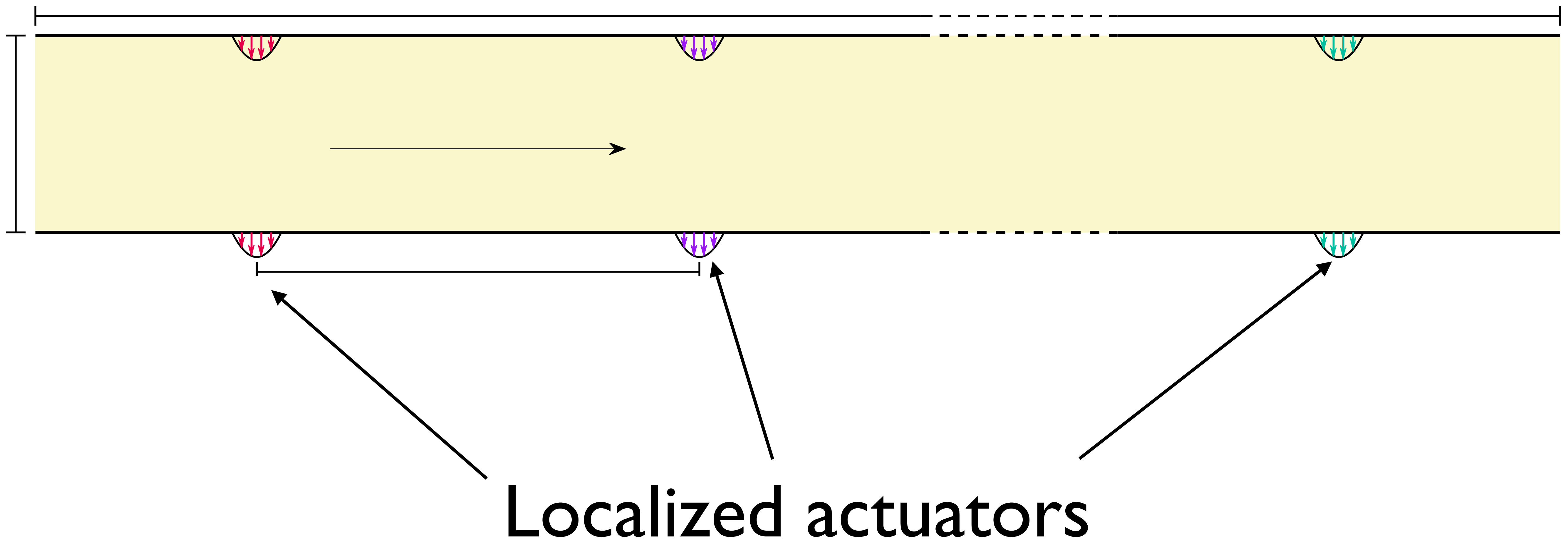
# Stabilization of flow over a circular cylinder

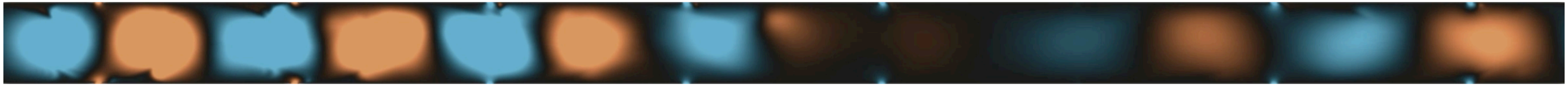
The identified control strategy achieves complete stabilization



# Stabilization of channel flow

We consider two-dimensional flow through a periodic channel (Re = 8000)

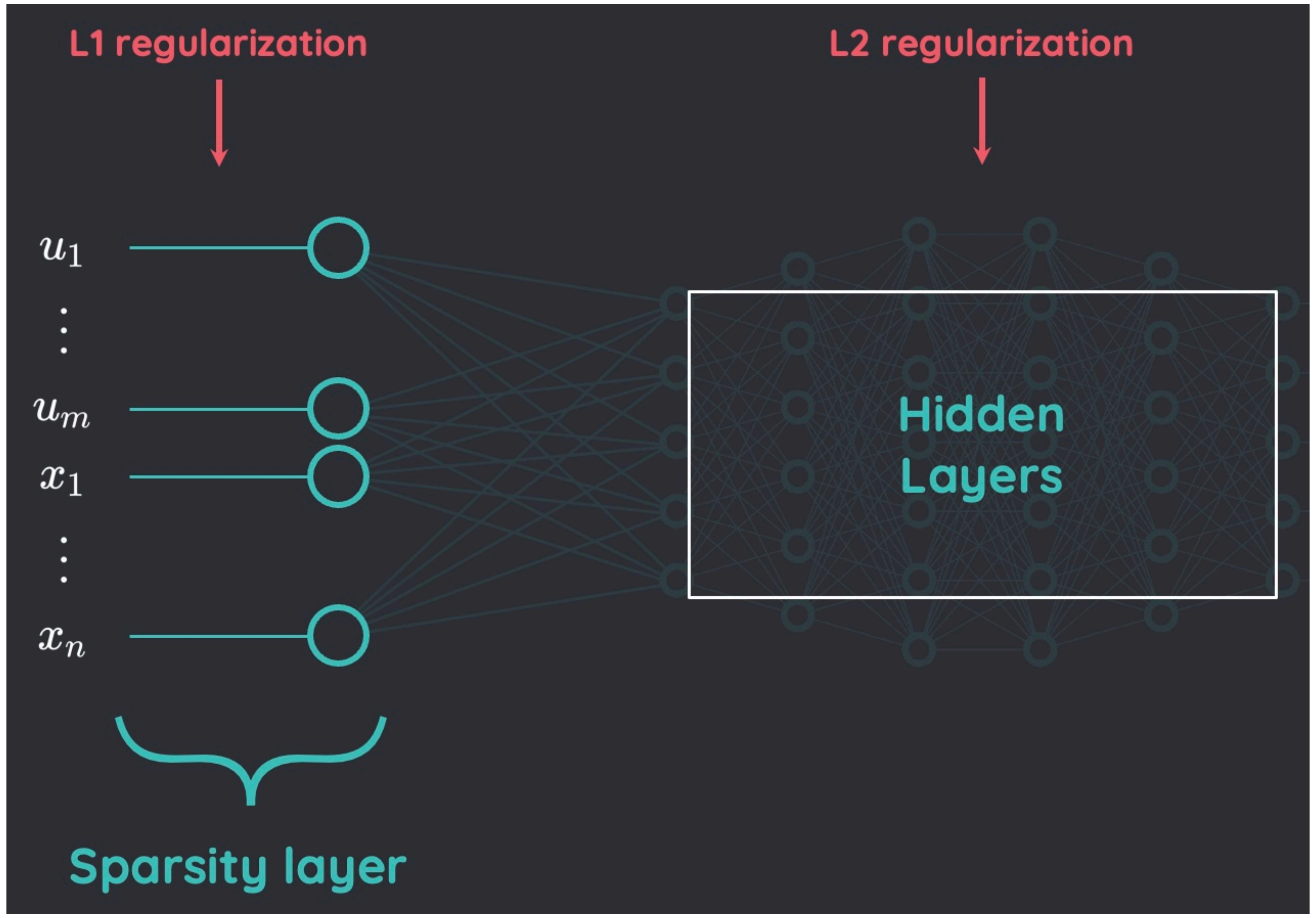


Complete stabilization is achieved

# Neural networks for flow analysis: choosing sensor locations

- Sensor selection from a candidate set can be achieved by the addition of a sparsity-promoting layer to the neural network, which used an L1 norm (rather than standard L2 norm)



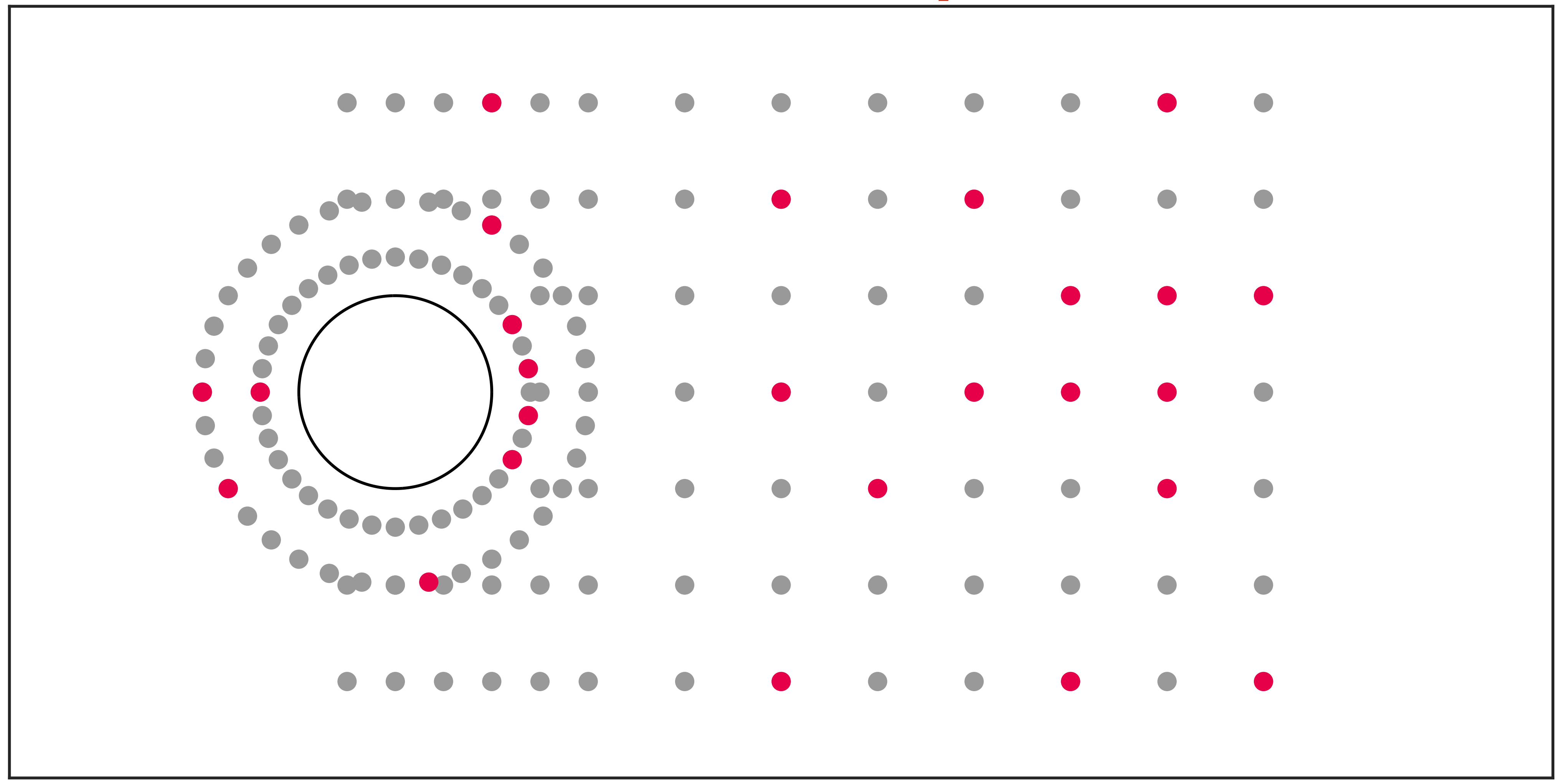

- Provides insight into the most important locations to collect data
- Reduces the overall size of the neural network

# Neural networks for flow analysis: choosing sensor locations

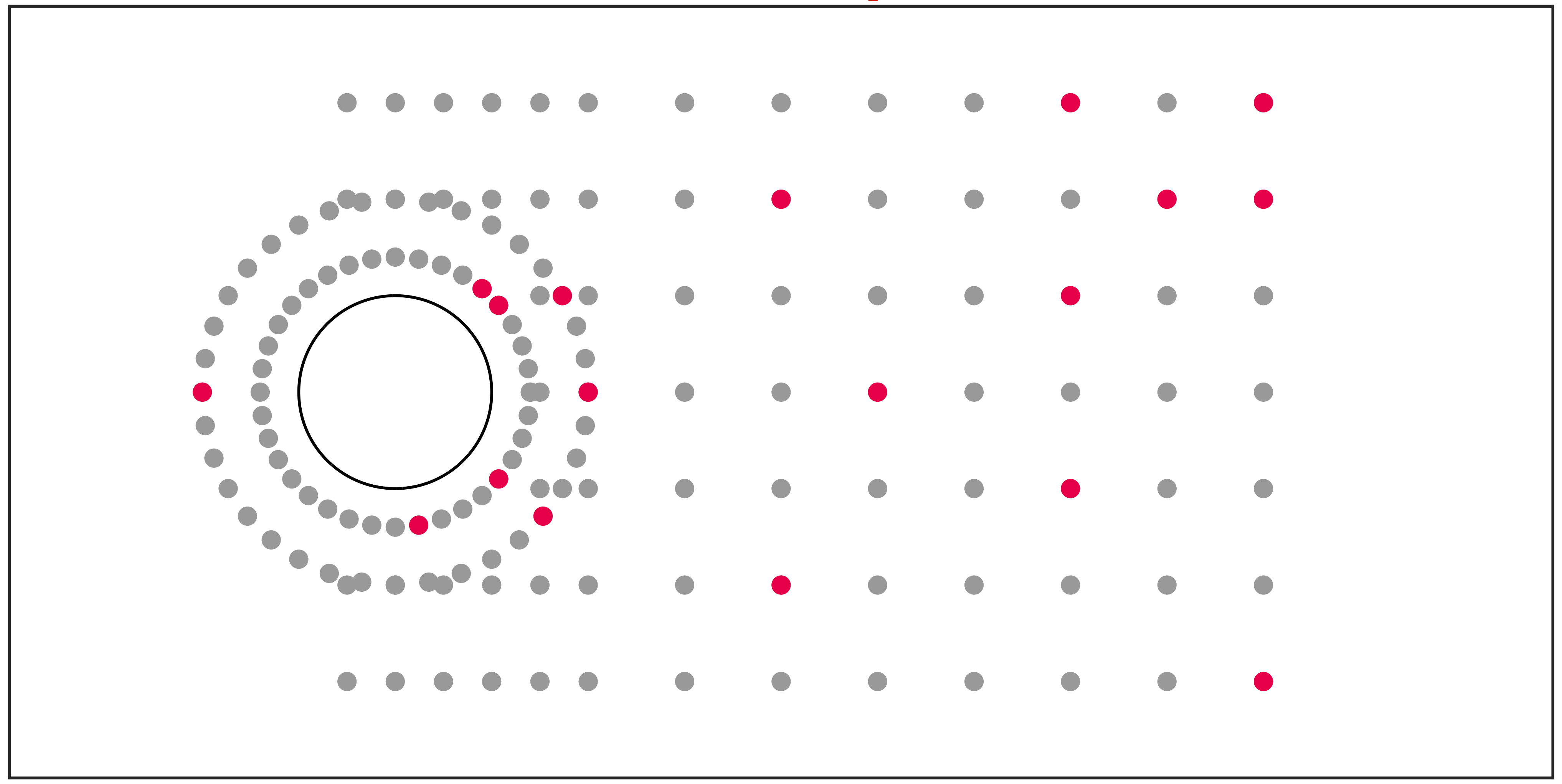
- Sensor selection from a candidate set can be achieved by the addition of a sparsity-promoting layer to the neural network, which used an L1 norm (rather than standard L2 norm)

Selected sensors for **cylinder flow**

Horizontal velocity sensors



Vertical velocity sensors



# Neural networks for flow analysis: choosing sensor locations

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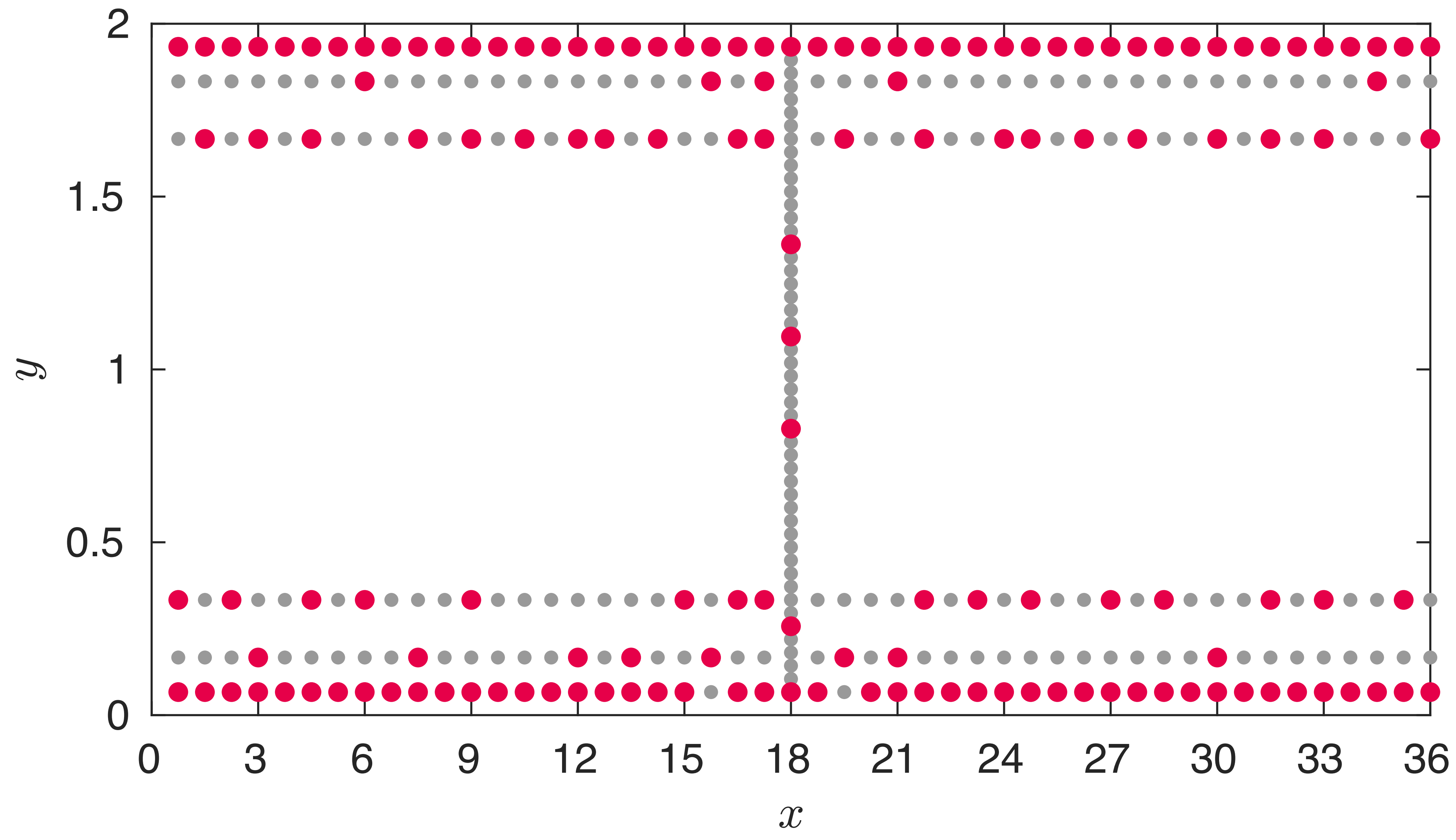
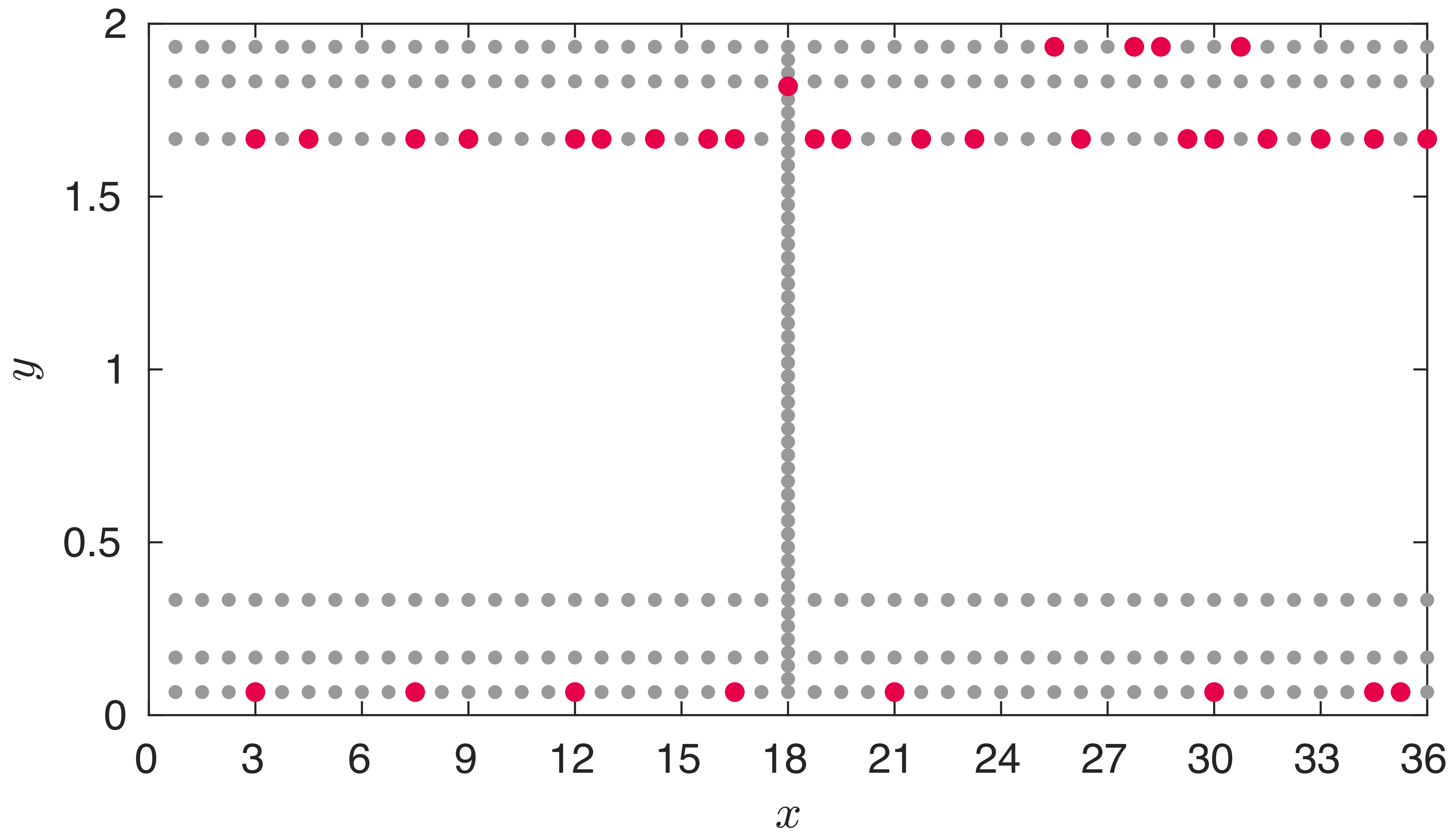
Selected sensors for **channel flow**

Horizontal velocity sensors




Vertical velocity sensors

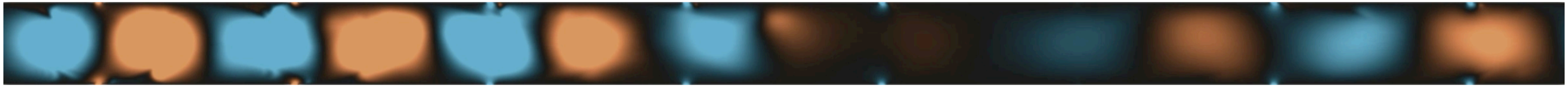


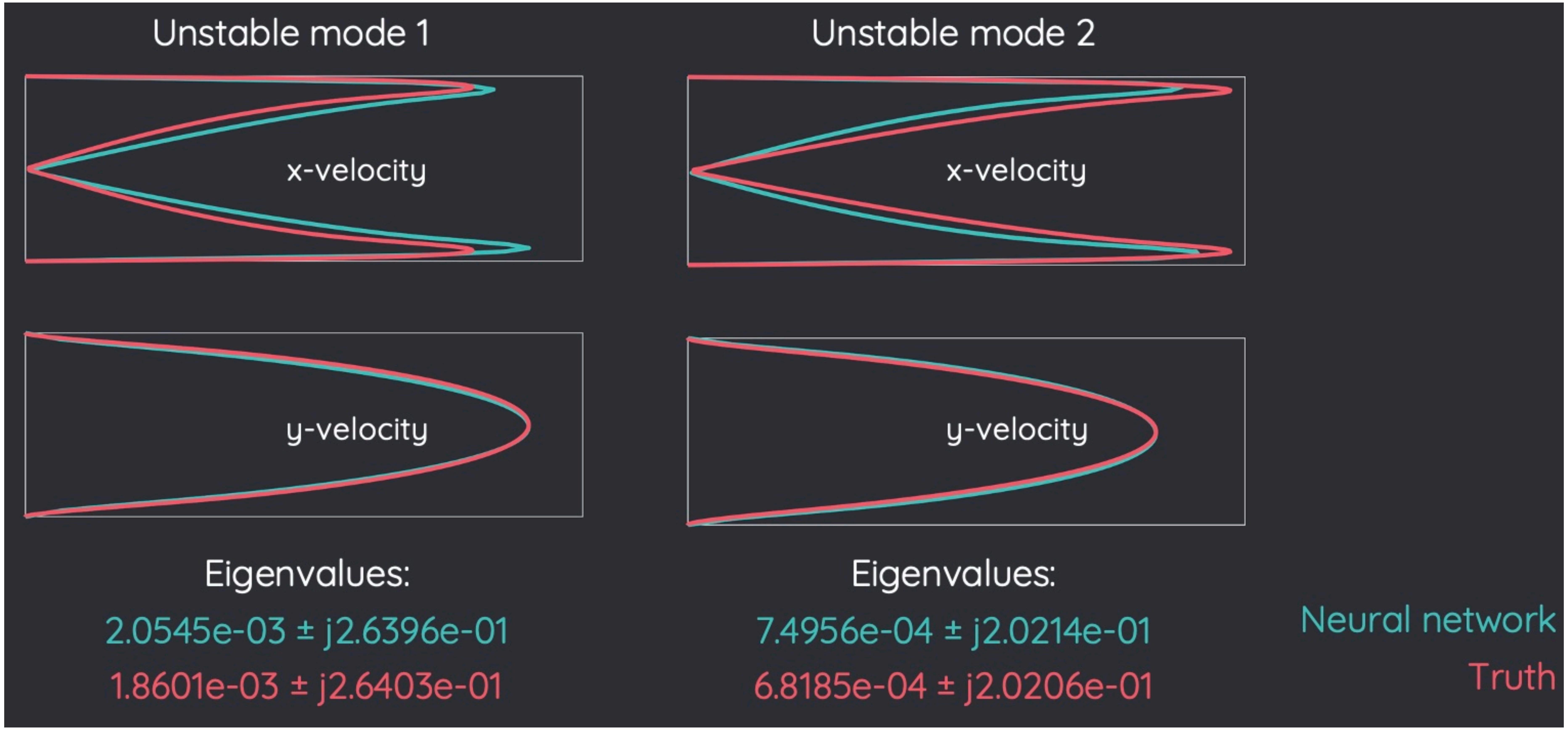
# Neural networks for flow analysis: linear stability analysis

- To understand the mechanisms by which a fluid flow becomes unstable (and eventually transitions to turbulence), we can study the properties of the **linearized system** near a (stable or unstable) equilibrium
- This is typically done by explicitly forming, discretizing, and decomposing the linearized governing equations
- We can instead use our identified neural network models to perform this analysis in two ways:
  - Use the fact that neural networks are easily differentiable to **linearize the global neural network model**
  - By applying control, we can generate a rich set of near-equilibrium data, which can be used to **identify a separate linear model**

# Neural networks for flow analysis: linear stability analysis

## Neural network stability analysis of 2D channel flow





# Other methods for flow control

- **Linear control theory** [Bagheri et al. 2009, Semeraro et al. 2013, Belson et al. 2013, Leclercq et al. 2019]

- **Reinforcement learning** [Rabault et al. 2019, Fan et al. 2020, Ren et al. 2021, Guastoni et al, 2023]

- **Genetic algorithms** [Rabaudo et al. 2020, Zigunov et al. 2022]

- Model predictive control

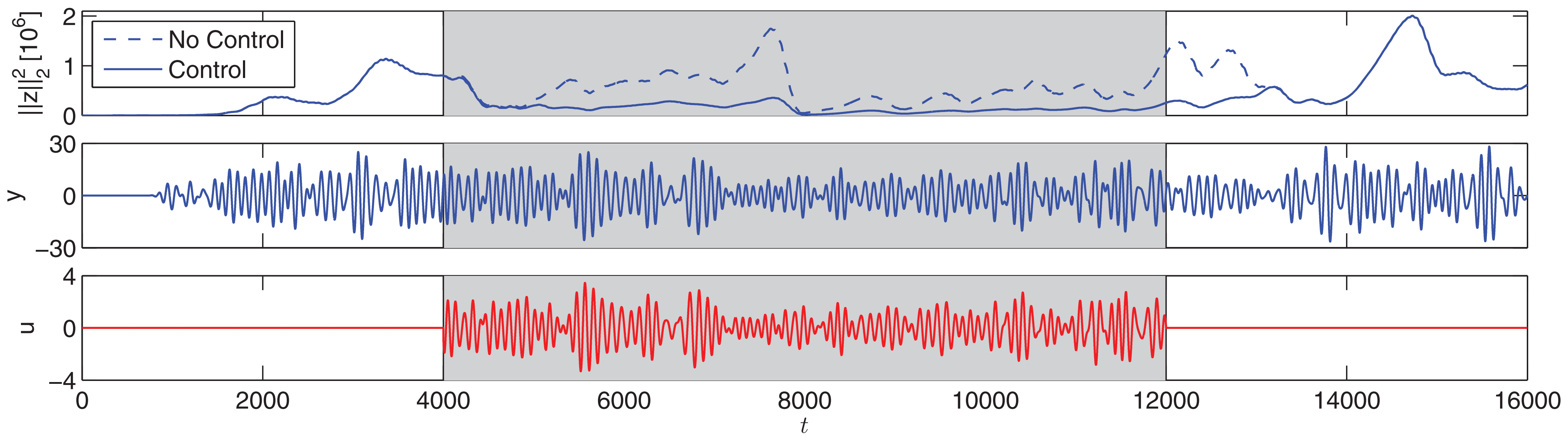
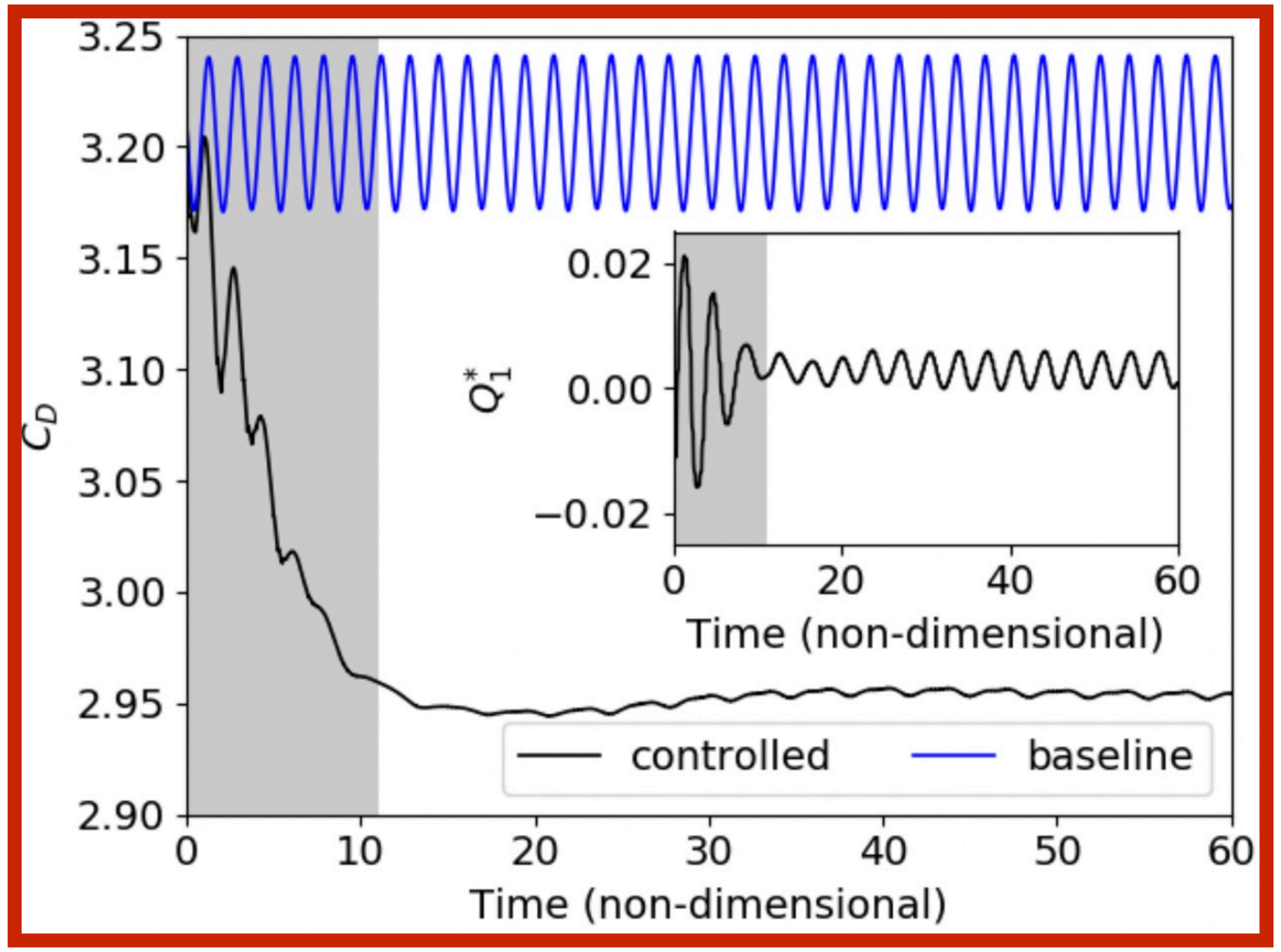



FIG. 14. Input and output signals of PI feedback controlled full system with the new actuator, Eq. (16), and a stream-wise velocity point sensor centered at $x_y = 405$ (feedback). The control is on from $t = 4000$ to 12000, the grey region. The disturbance signal, w, is the same as in Figure 9.



# Conclusions

- Simple neural networks (dense networks, ReLU activation functions, 1-2 hidden layers) can be effective for both surrogate models for nonlinear fluid flows, and for nonlinear controllers
- The effectiveness of this method relies on an iterative training strategy that generates large quantities of data in regions of state space that are most important for successful control (near desired equilibria)
- These neural network models/controllers can be further utilized to perform common flow analysis tasks

# Future work

- Control more complex flows
- Apply in experimental setting

Deda, Wolf, & Dawson, "Backpropagation of neural network dynamical models applied to flow control," Theoretical and Computational Fluid Dynamics, 2023.