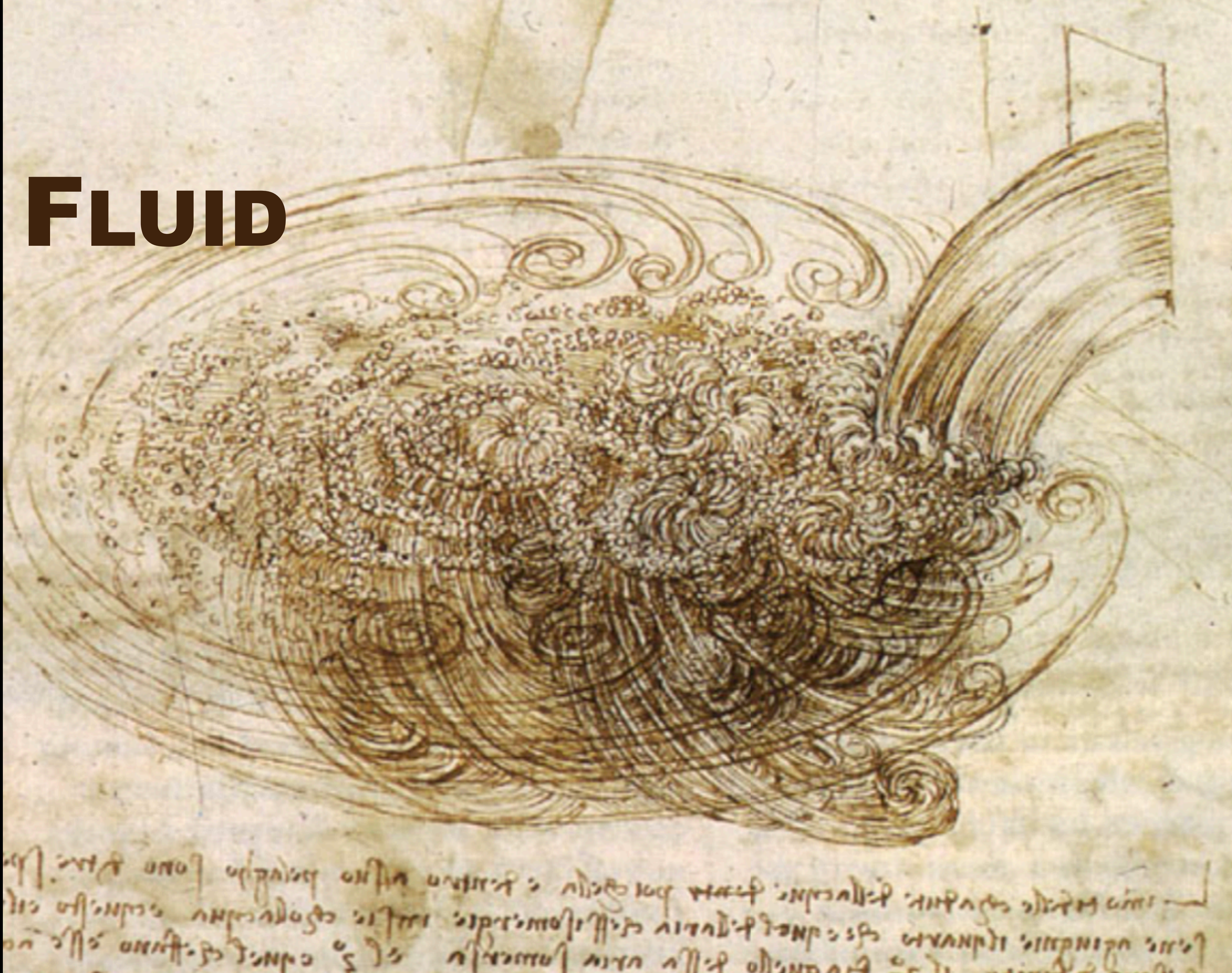
Fluid



COMPLEXIT

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\,\mathbf{u} = -\nabla p + \boxed{\frac{1}{\mathrm{Re}}}\nabla^2 \mathbf{u}$$

$$\nabla \cdot \mathbf{u} = 0$$

**Increasi
ng
Reynold**

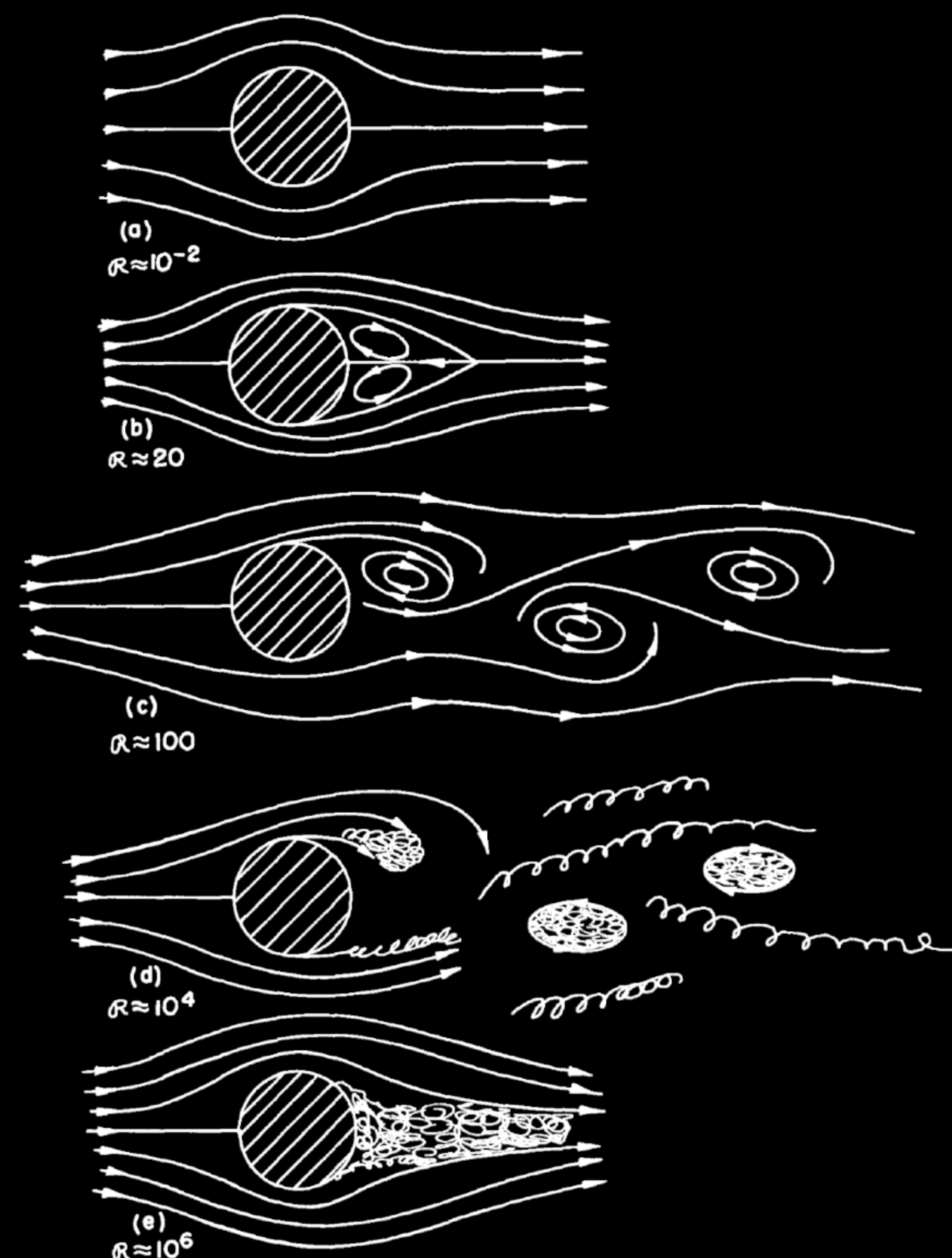


Fig. 41–6. Flow past a cylinder for various Reynolds numbers.

Feynman Lectures II

COMPLEXIT

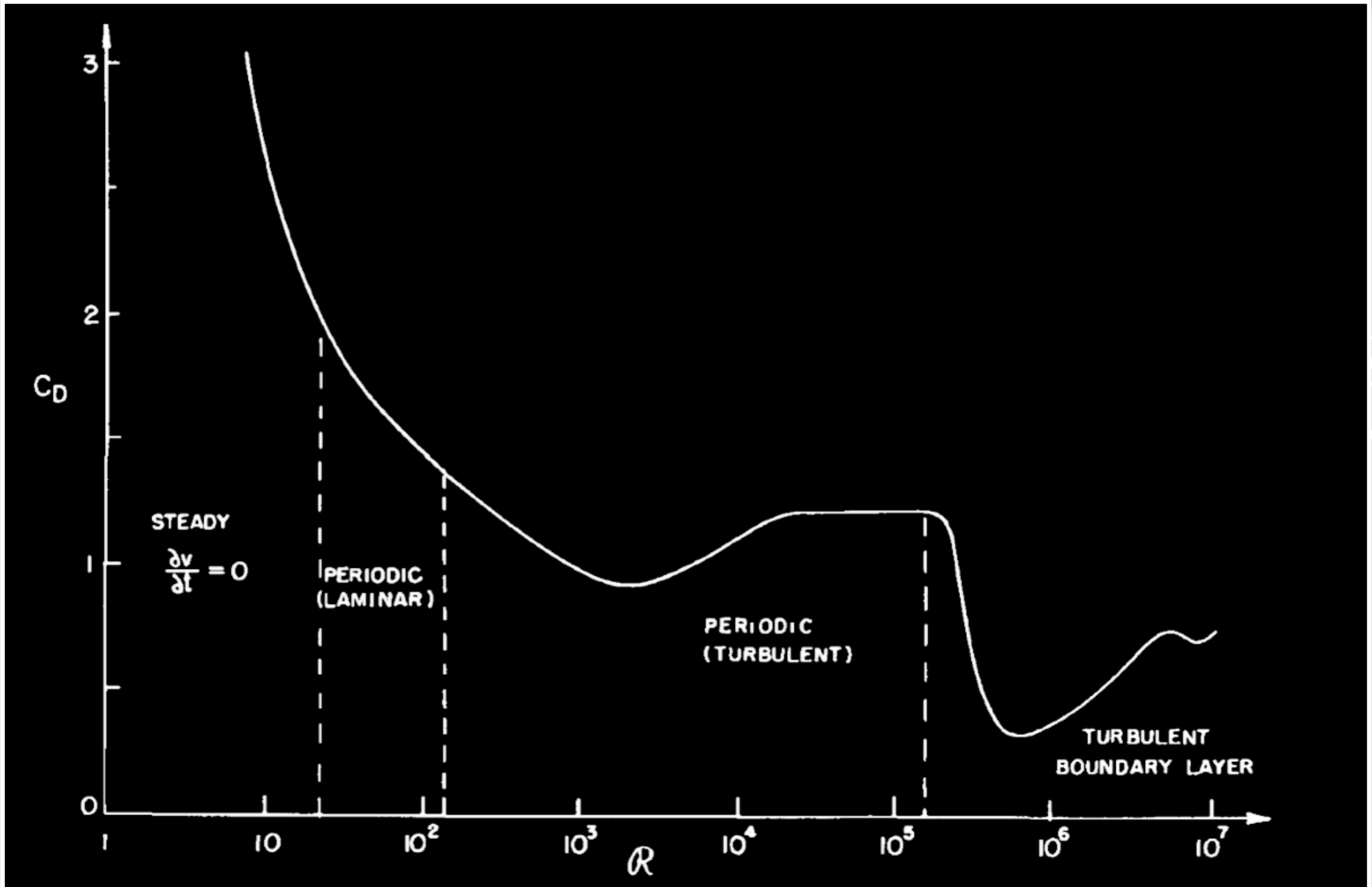


Fig. 41–4. The drag coefficient C_D of a circular cylinder as a function of the Reynolds number.

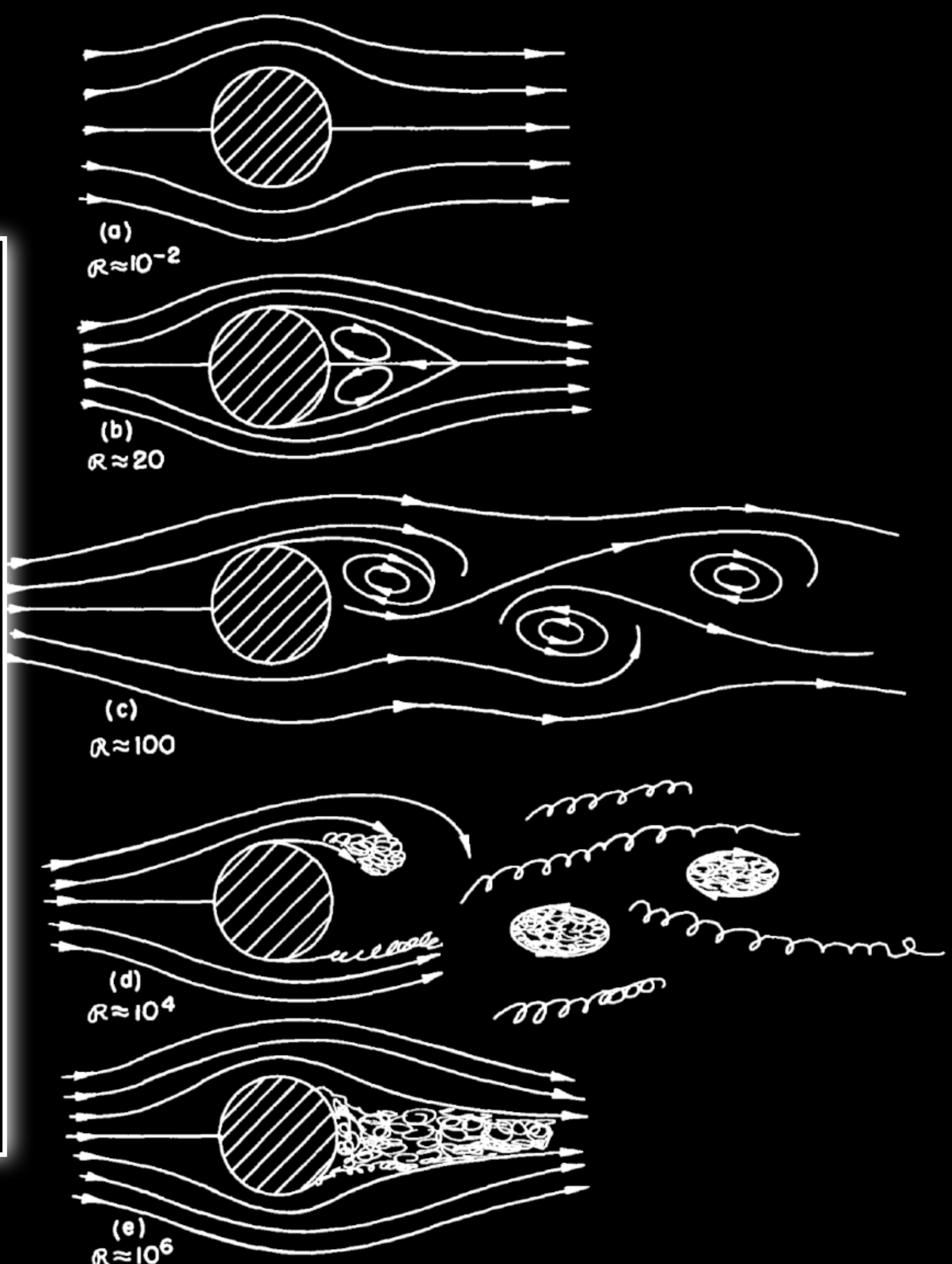
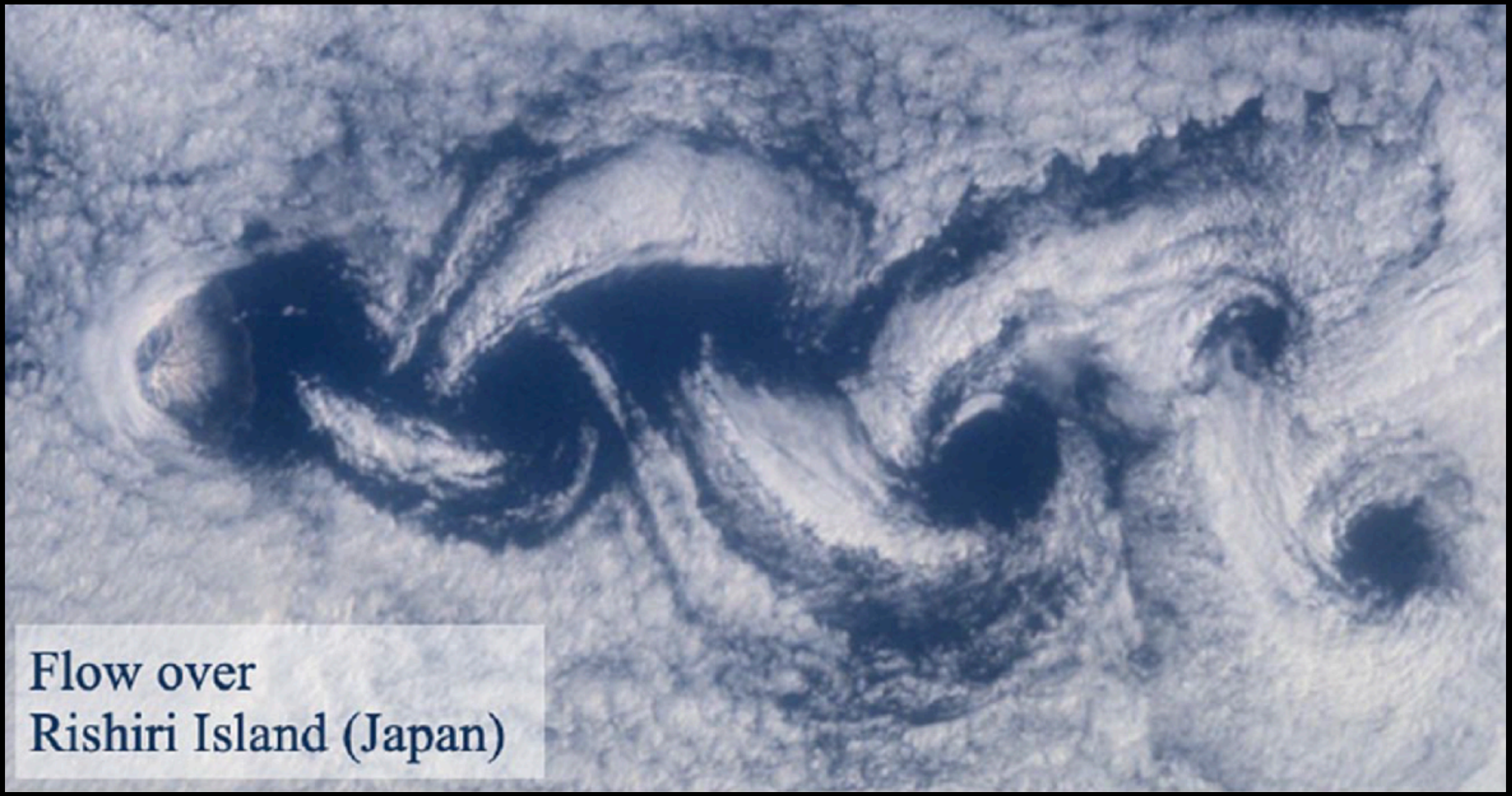


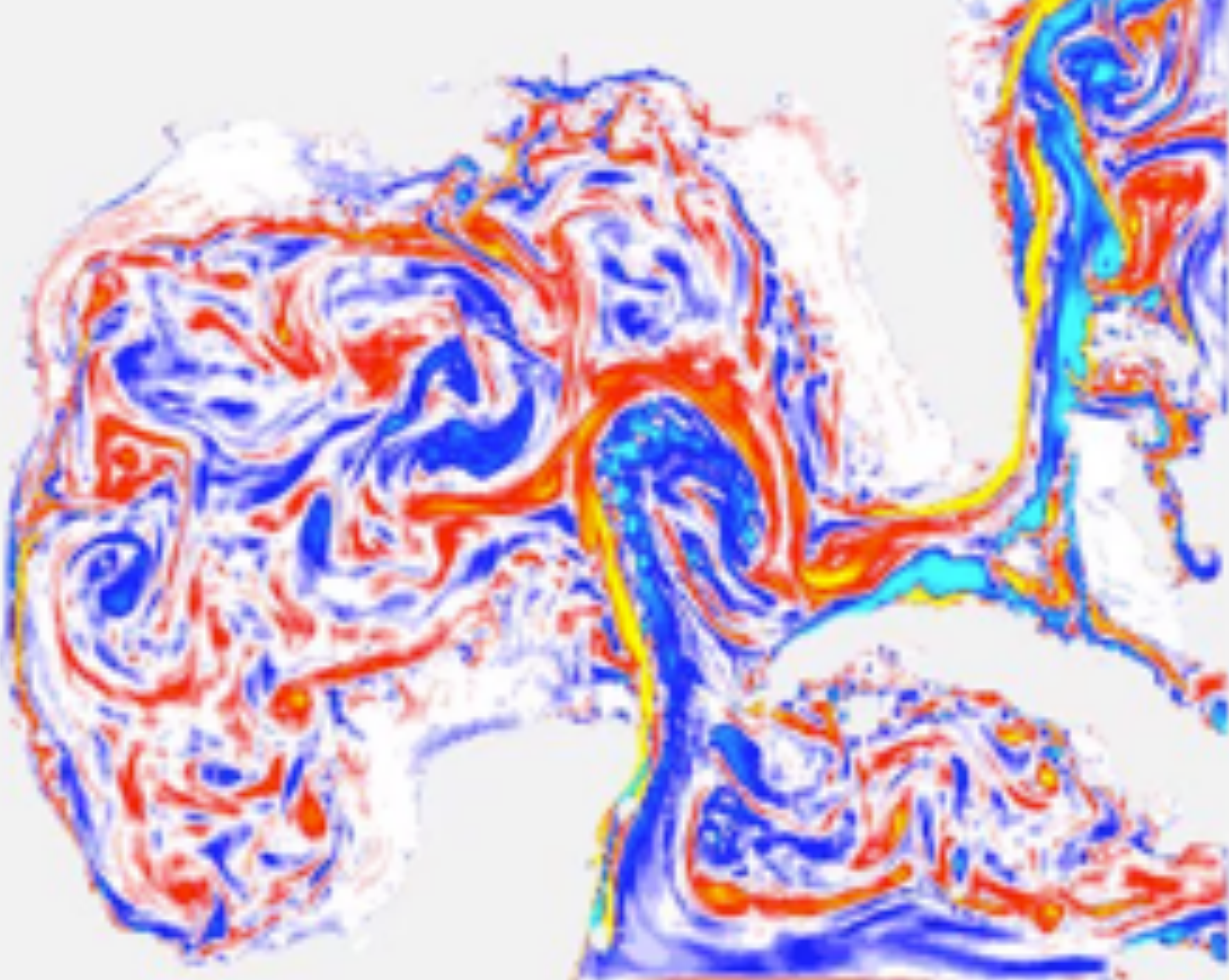
Fig. 41–6. Flow past a cylinder for various Reynolds numbers.

Feynman Lectures II


Flow over
Rishiri Island (Japan)

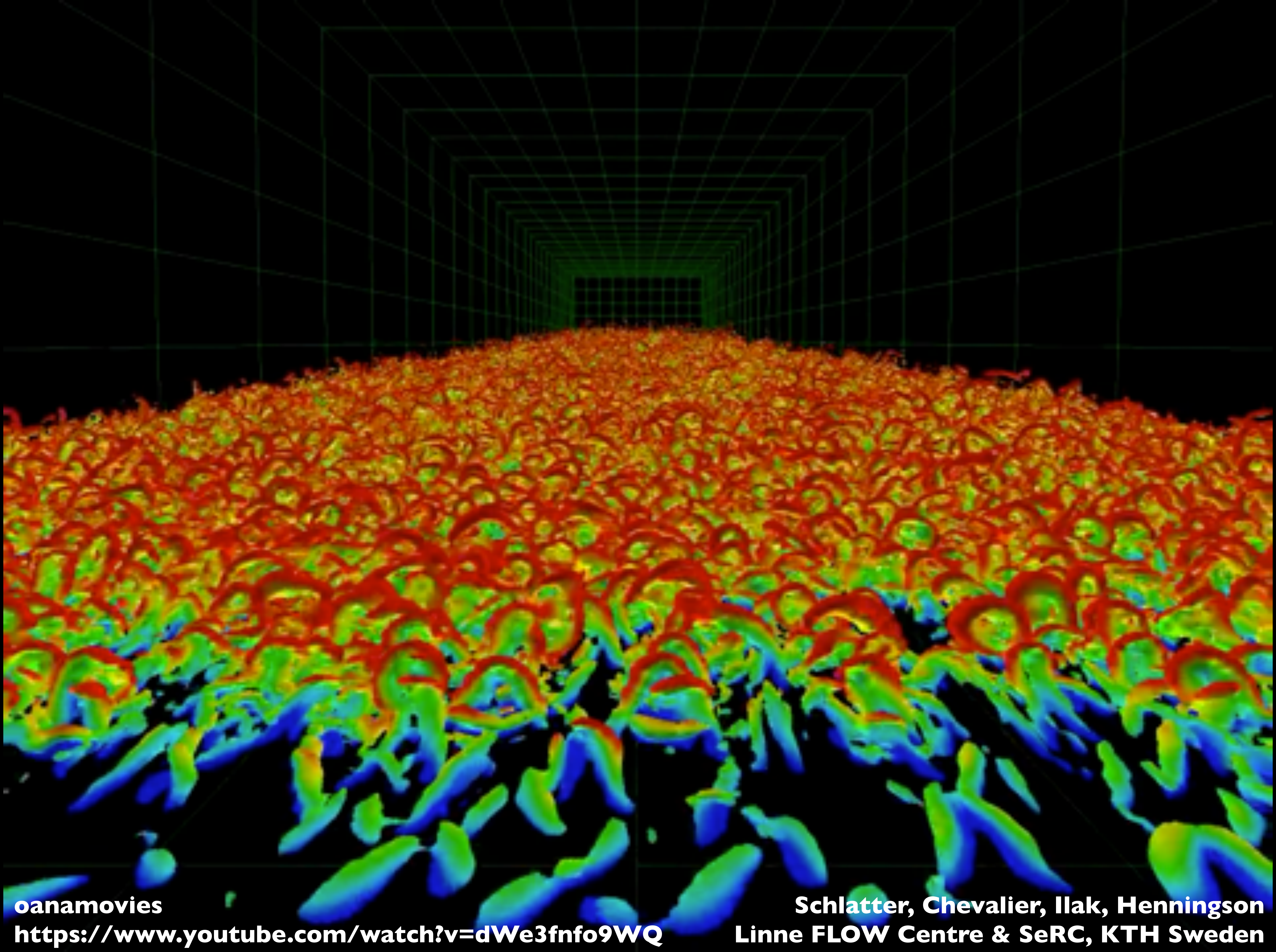

Flow over a cylinder
(*Re* = 100)

HYCOM.org



Ocean Next
https://www.youtube.com/watch?v=fNEEHyrCUG0

turbulenceteam https://www.youtube.com/watch?v=OM0l2YPVMf8


oanamovies
https://www.youtube.com/watch?v=dWe3fnfo9WQ
Schlatter, Chevalier, Ilak, Henningson
Linne FLOW Centre & SeRC, KTH Sweden

We have written the equations of water flow. From experiment, we find a set of concepts and approximations to use to discuss the solution—vortex streets, turbulent wakes, boundary layers. When we have similar equations in a less familiar situation, and one for which we cannot yet experiment, we try to solve the equations in a primitive, halting, and confused way to try to determine what new qualitative features may come out, or what new qualitative forms are a consequence of the equations. Our equations for the sun, for example, as a ball of hydrogen gas, describe a sun without sunspots, without the rice-grain structure of the surface, without prominences, without coronas. Yet, all of these are really in the equations; we just haven't found the way to get them out.

There are those who are going to be disappointed when no life is found on other planets. Not I—I want to be reminded and delighted and surprised once again, through interplanetary exploration, with the infinite variety and novelty of phenomena that can be generated from such simple principles. The test of science is its ability to predict. Had you never visited the earth, could you predict the thunderstorms, the volcanos, the ocean waves, the auroras, and the colorful sunset? A salutary lesson it will be when we learn of all that goes on on each of those dead planets—those eight or ten balls, each agglomerated from the same dust cloud and each obeying exactly the same laws of physics.

The next great era of awakening of human intellect may well produce a method of understanding the *qualitative* content of equations. Today we cannot. Today we cannot see that the water flow equations contain such things as the barber pole structure of turbulence that one sees between rotating cylinders. Today we cannot see whether Schrödinger's equation contains frogs, musical composers, or morality —or whether it does not. We cannot say whether something beyond it like God is needed, or not. And so we can all hold strong opinions either way.

Feynman Lectures II

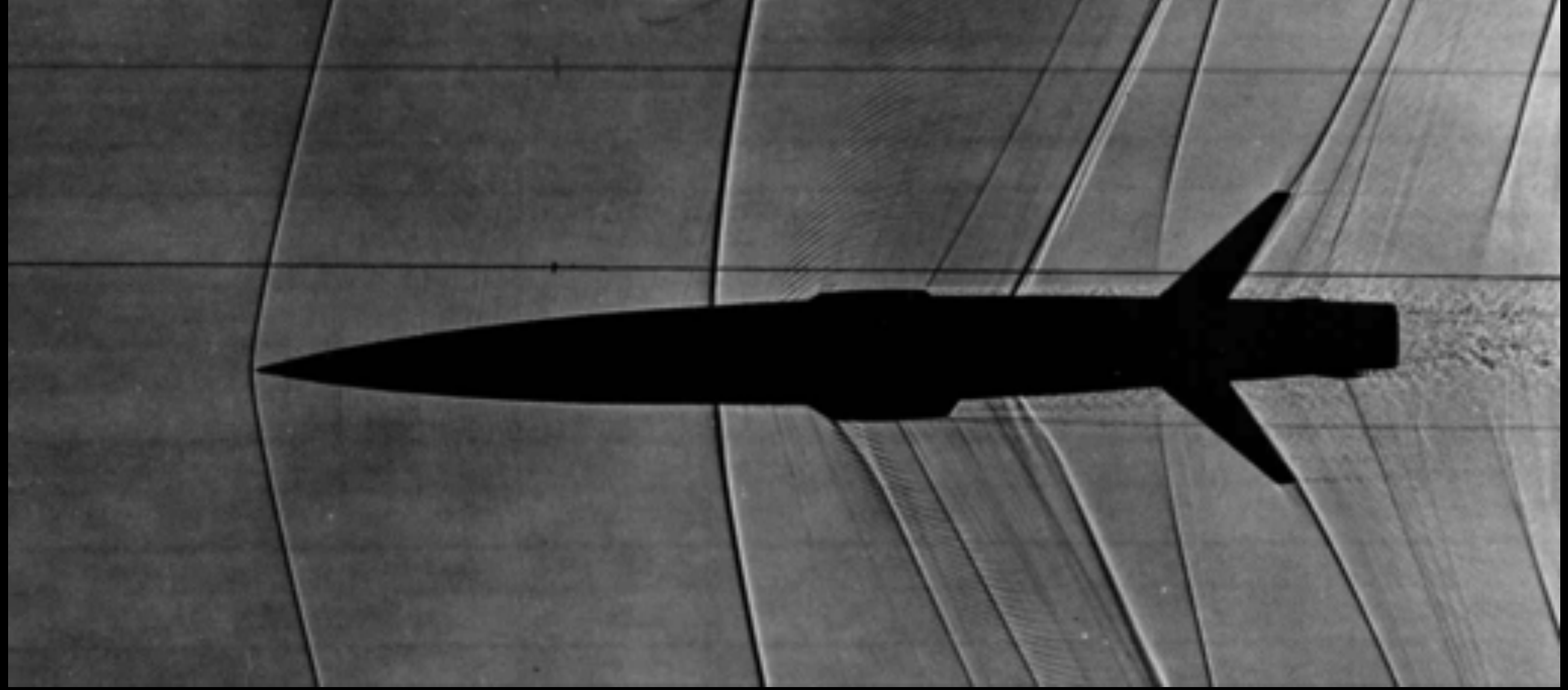
CANONICAL FLOWS

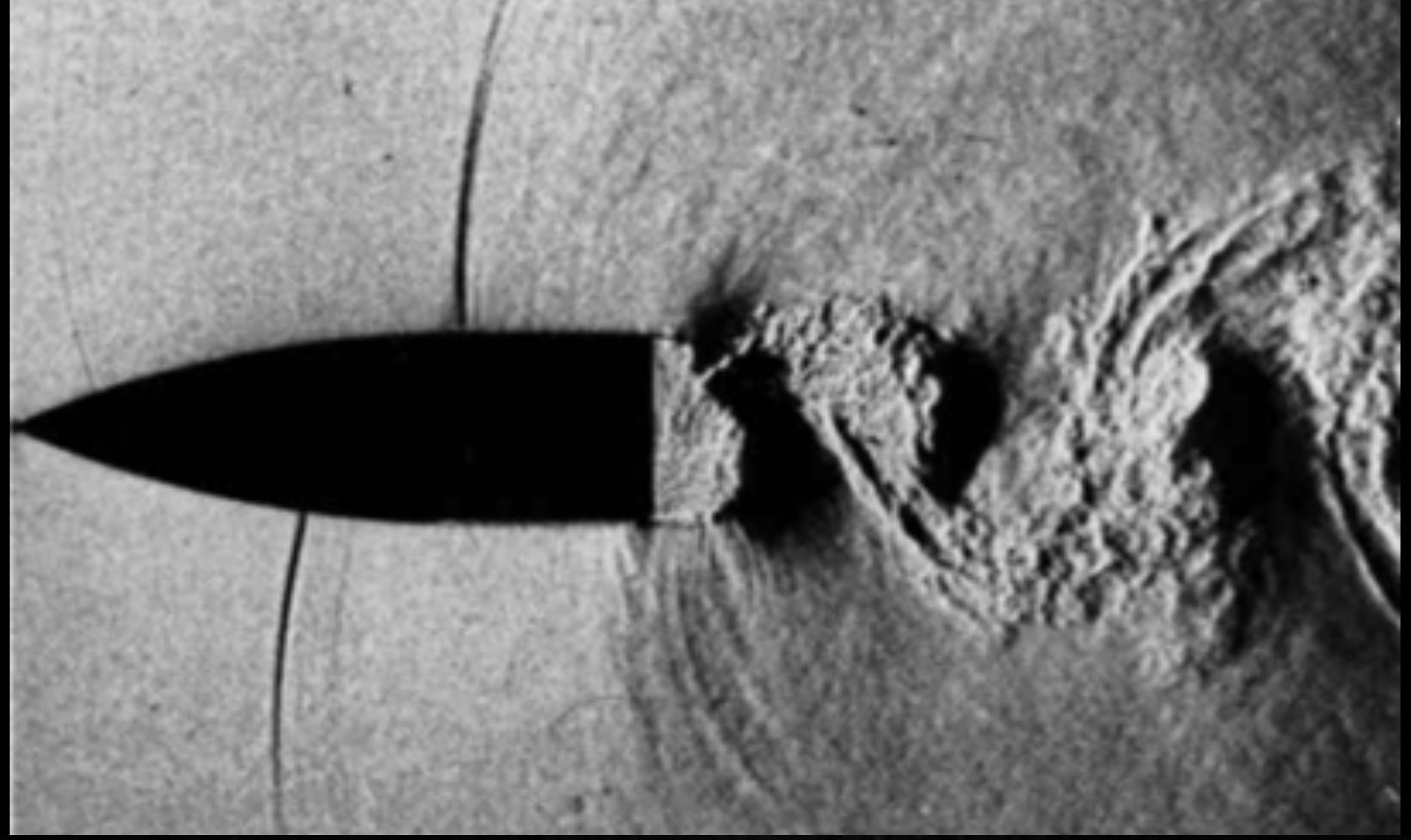
An Album of Fluid Motion

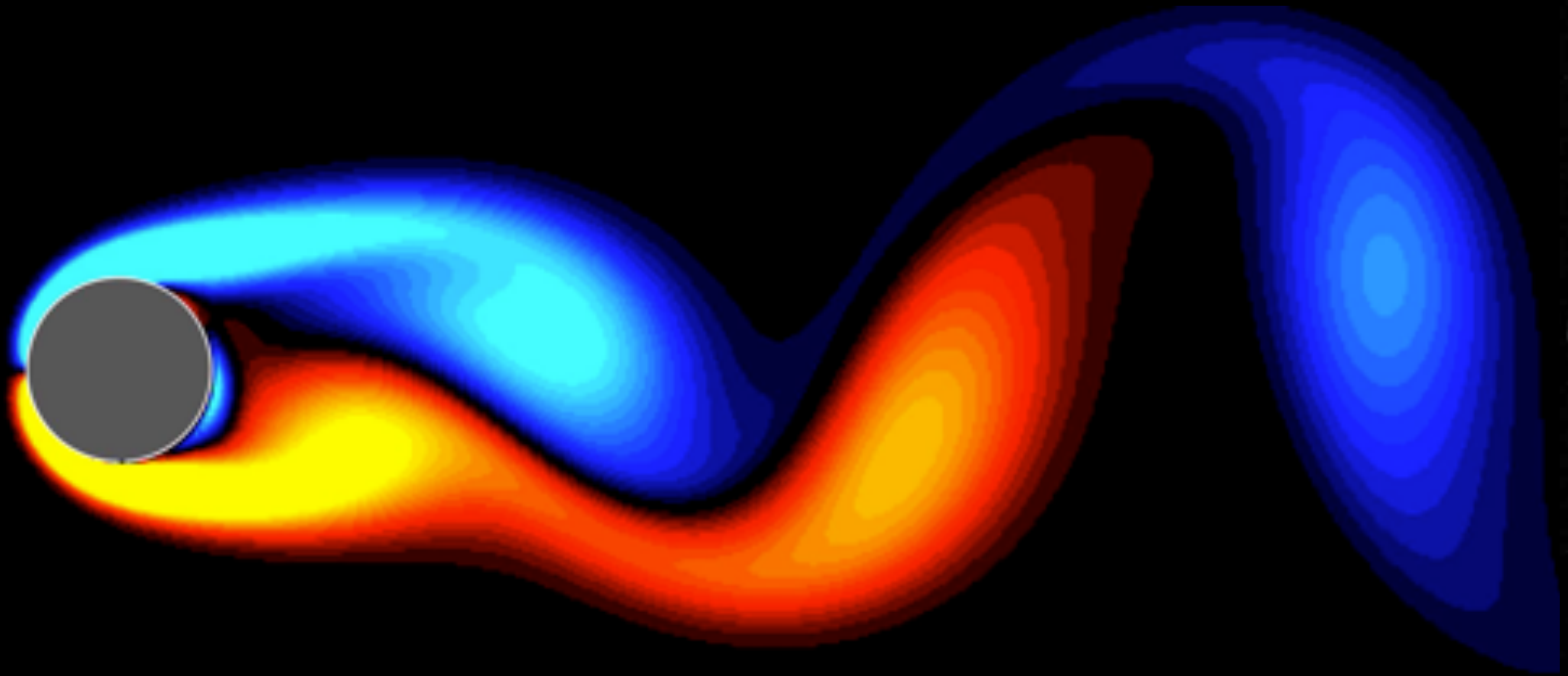
- Jet
- Wake
- Cavity
- Channel
- Pipe flow
- Mixing Layer
- Boundary Layer
- Wall bounded flows
- Isotropic turbulence

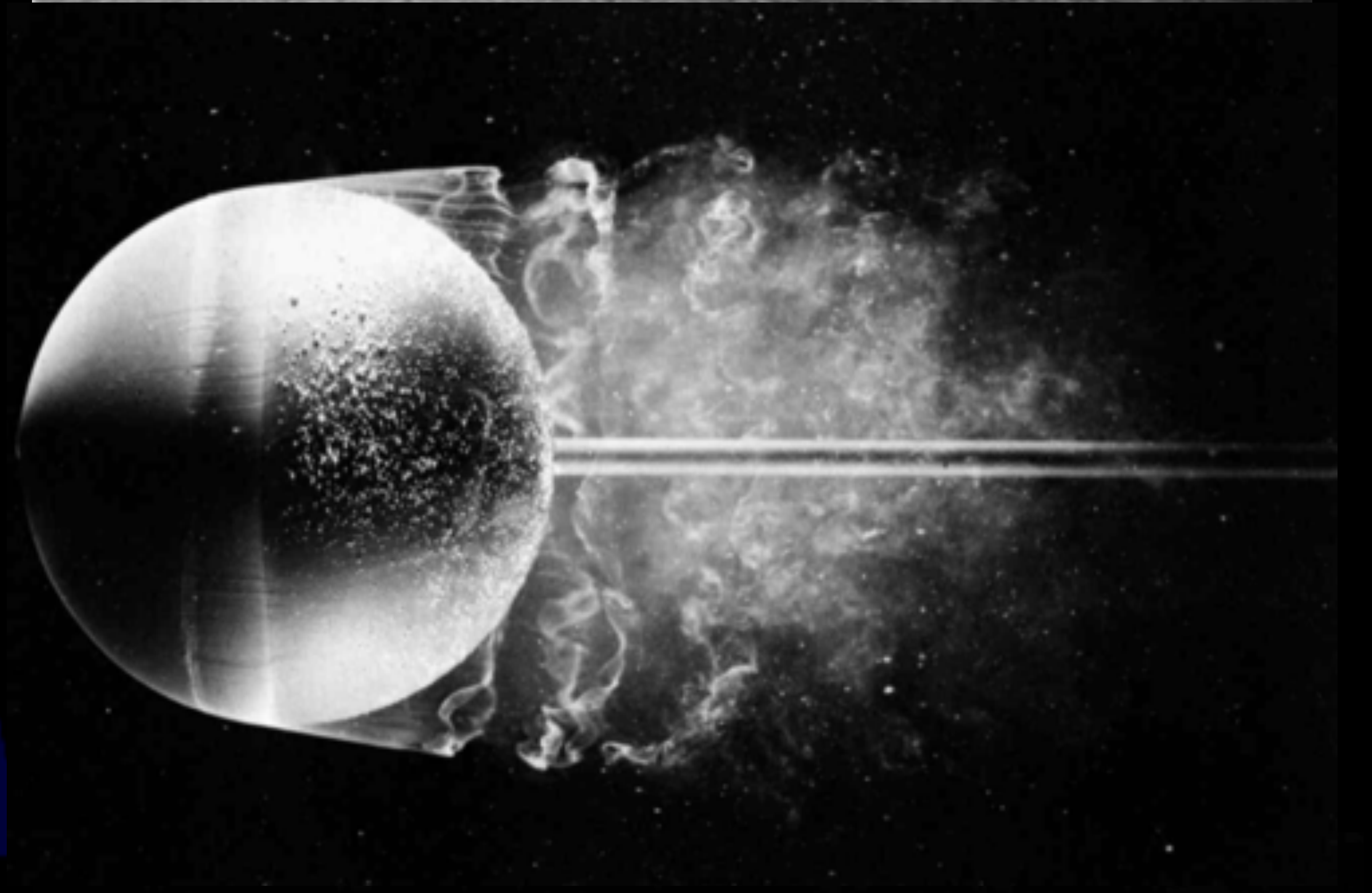
Milton Van Dyke

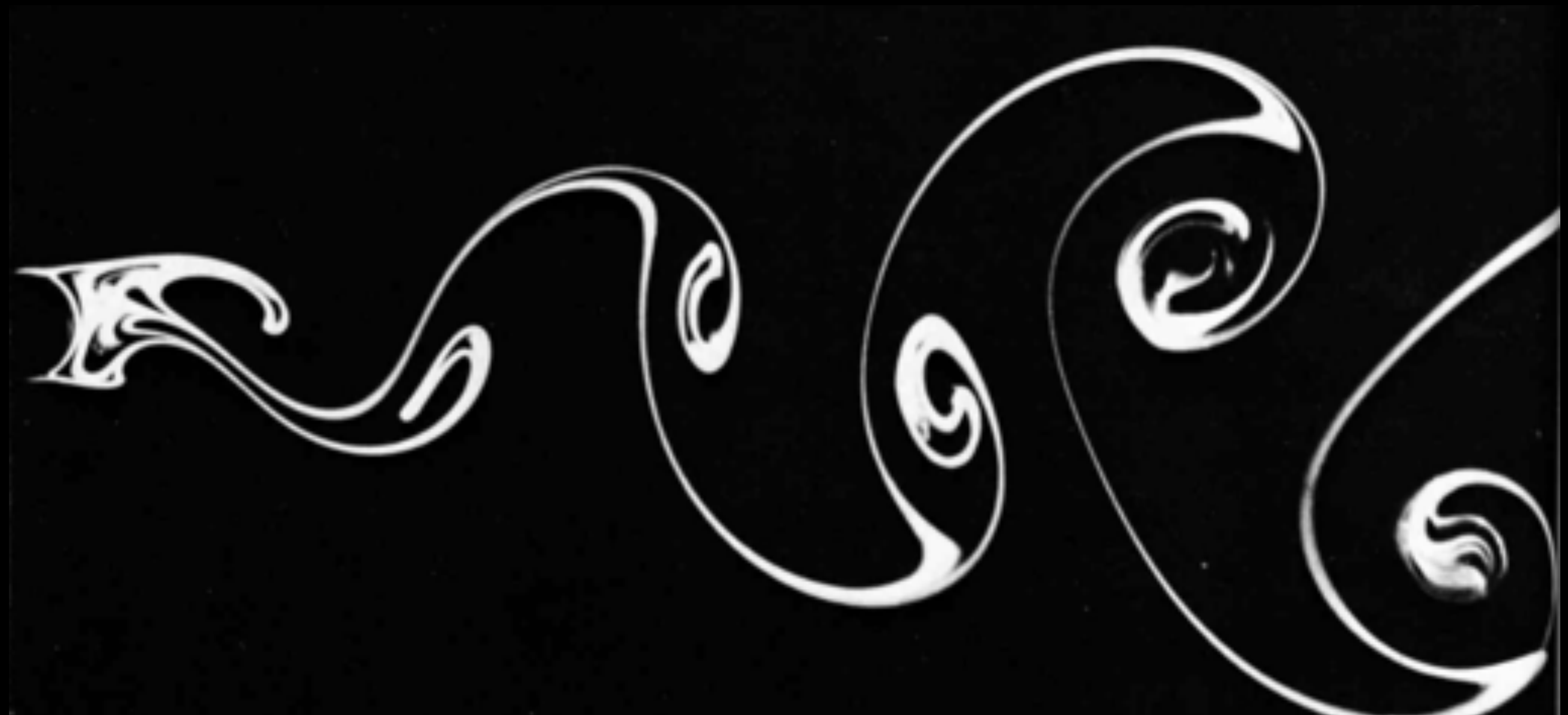
WAKES





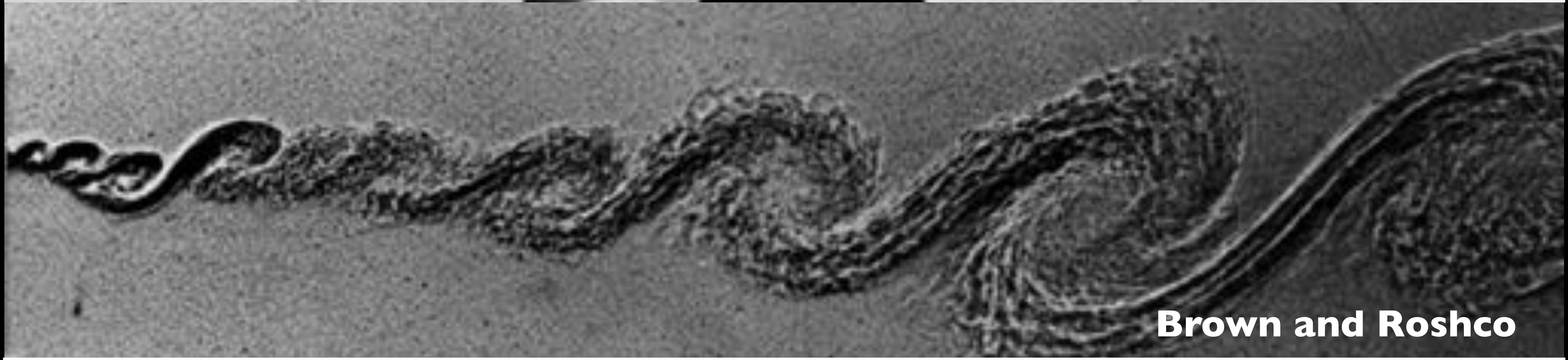






Milton Van Dyke

Milton Van Dyke

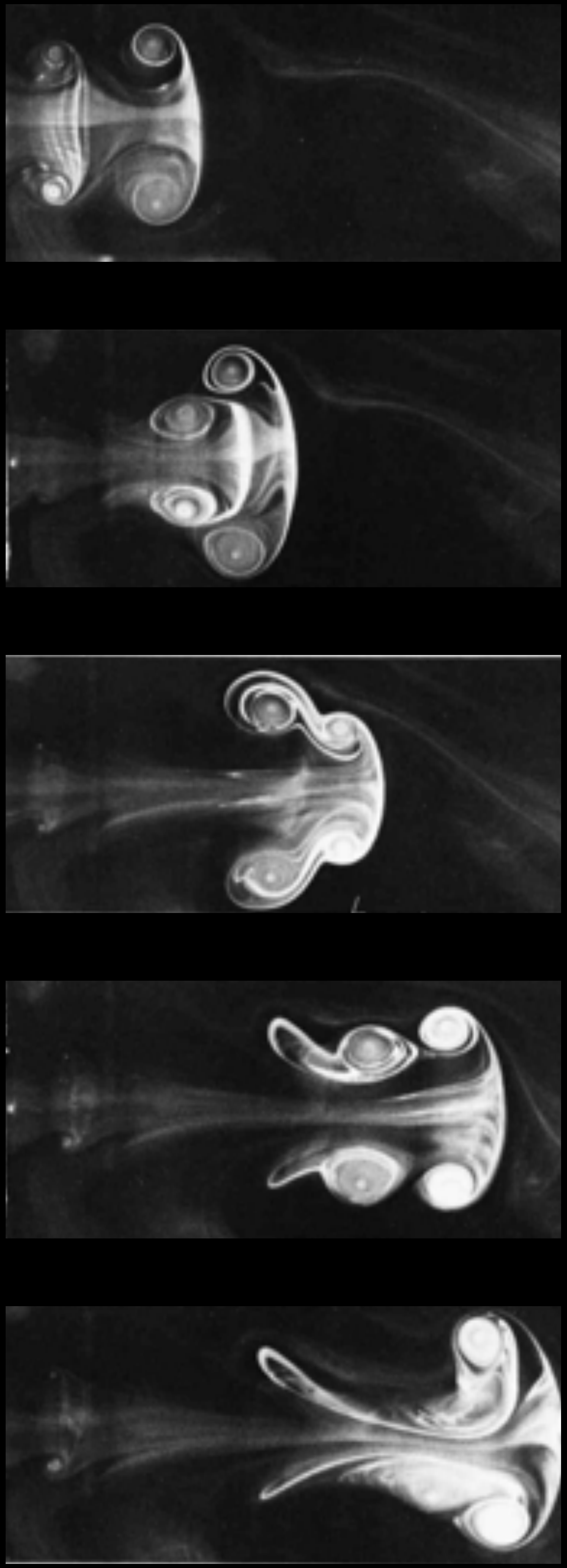


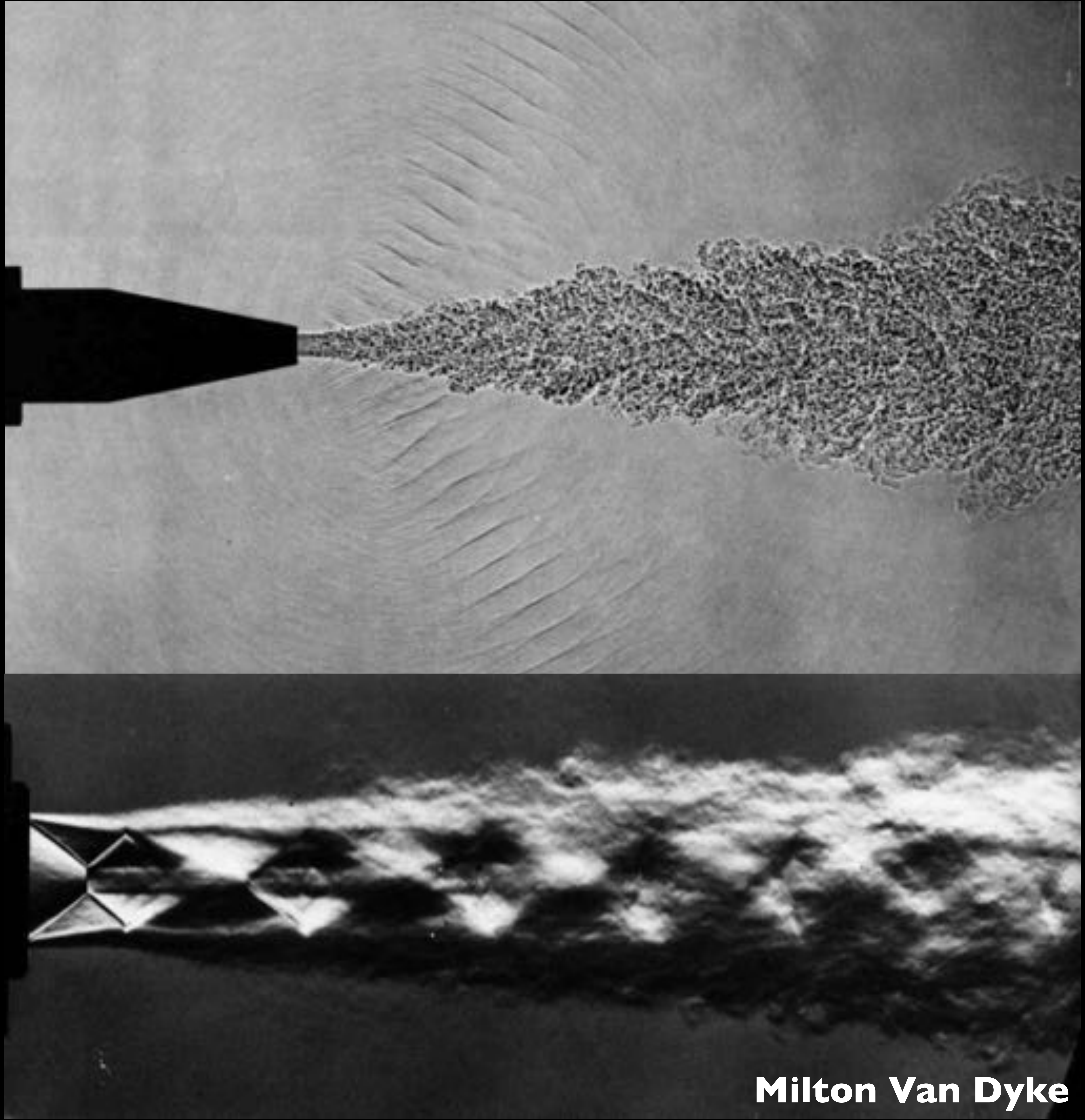
Brown and Roshco

Callaham, Maeda, SLB

MIXING LAYERS

JETS



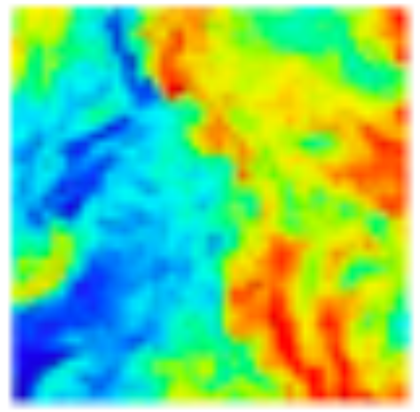


Milton Van Dyke

DATABASES

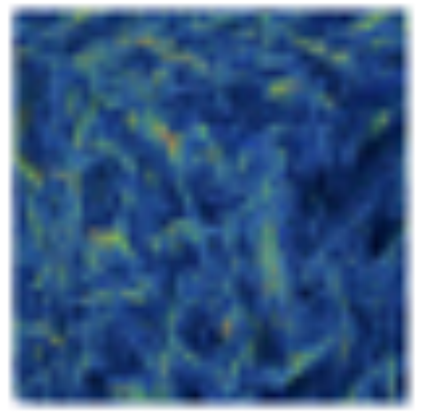
Johns Hopkins Turbulence Databases

Dataset descriptions



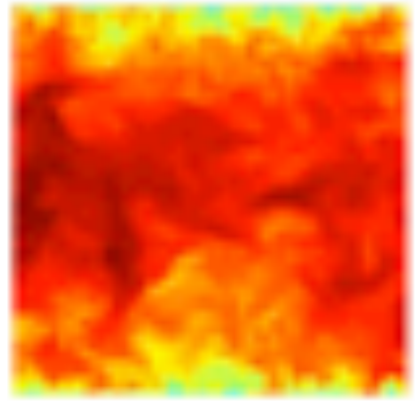
1. Forced isotropic turbulence:

Direct numerical simulation (DNS) using $1{,}024^3$ nodes. The full time evolution is available, over 5 large-scale turnover times.



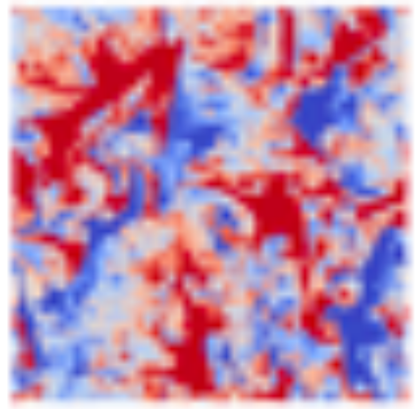
2. Forced MHD turbulence:

Direct numerical simulation (DNS) of magneto-hydrodynamic isotropic turbulence using $1{,}024^3$ nodes. The full time evolution is available, over about 1 large-scale turnover time.



3. Channel flow:

Direct numerical simulation (DNS) of channel flow turbulence in a domain of size $8\pi \times 2 \times 3\pi$, using $2048 \times 512 \times 1536$ nodes. The full time evolution is available, over a flow-through time across across the 8π channel



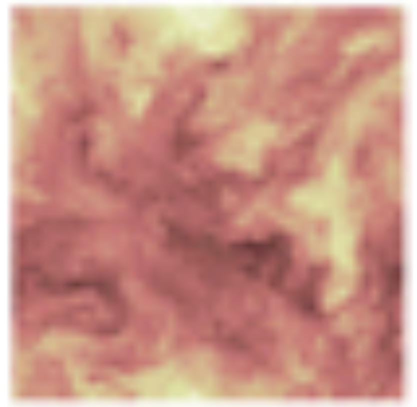
4. Homogeneous buoyancy driven turbulence:

Direct Numerical Simulation (DNS) of homogeneous buoyancy driven turbulence in a domain size $2\pi \times 2\pi \times 2\pi$, using $1{,}024^3$ nodes. The full time evolution is available, covering both the buoyancy driven increase in turbulence intensity as well as the buoyancy mediated turbulence decay.

Johns Hopkins Turbulence Databases

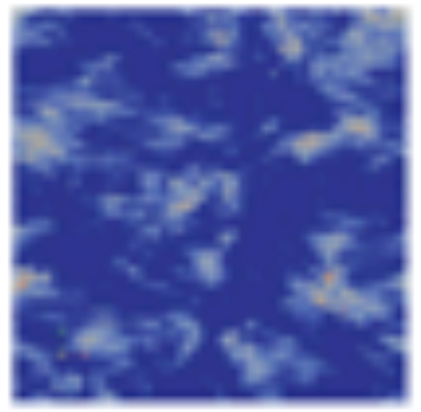
Home | Database Access | Documentation | Links | Visualizations | About

Dataset descriptions



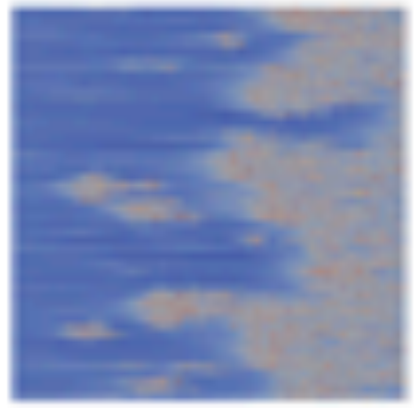
5. Forced isotropic turbulence dataset on 4096^3 Grid:

Direct numerical simulation (DNS) using 4096^3 nodes. A single timestep snapshot is available.



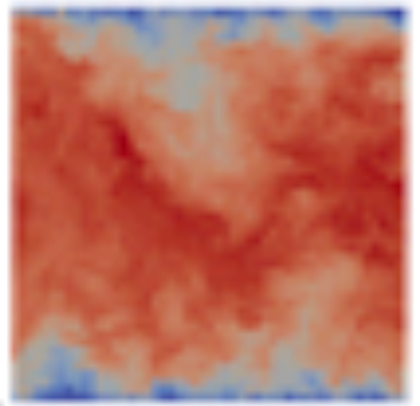
6. Rotating stratified turbulence dataset on 4096^3 Grid:

Direct numerical simulation (DNS) of rotating stratified turbulence using 4096^3 nodes. A total of 5 snapshots are available.



7. Transitional boundary layer:

Direct numerical simulation (DNS) of a transitional boundary layer using a finite volume DNS code. Data are stored on 3320 × 224 × 2048 grid points. The full time evolution is available, over about 1 flow-through time across the length of simulation domain.



8. Channel flow at Re_τ=5200:

Direct numerical simulation (DNS) of channel flow turbulence in a domain of size $8\pi \times 2 \times 3\pi$, using 10240 × 1536 × 7680 nodes. A total of 11 snapshots are available.

Johns Hopkins Turbulence Databases

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Burger, Treib, Westermann, Werner,
Lalescu, Szalay, Meneveau, Eying

Entry #: 84174

Vortices within vortices: hierarchical nature of vortex tubes in turbulence

Kai Bürger[1], Marc Treib[1], Rüdiger Westermann[1],
Suzanne Werner[2], Cristian C Lalescu[3],
Alexander Szalay[2], Charles Meneveau[4], Gregory L Eyink[2,3,4]

[1] Informatik 15 (Computer Graphik & Visualisierung), Technische Universität München
[2] Department of Physics & Astronomy, The Johns Hopkins University
[3] Department of Applied Mathematics & Statistics, The Johns Hopkins University
[4] Department of Mechanical Engineering, The Johns Hopkins University

MIXING

Plunge

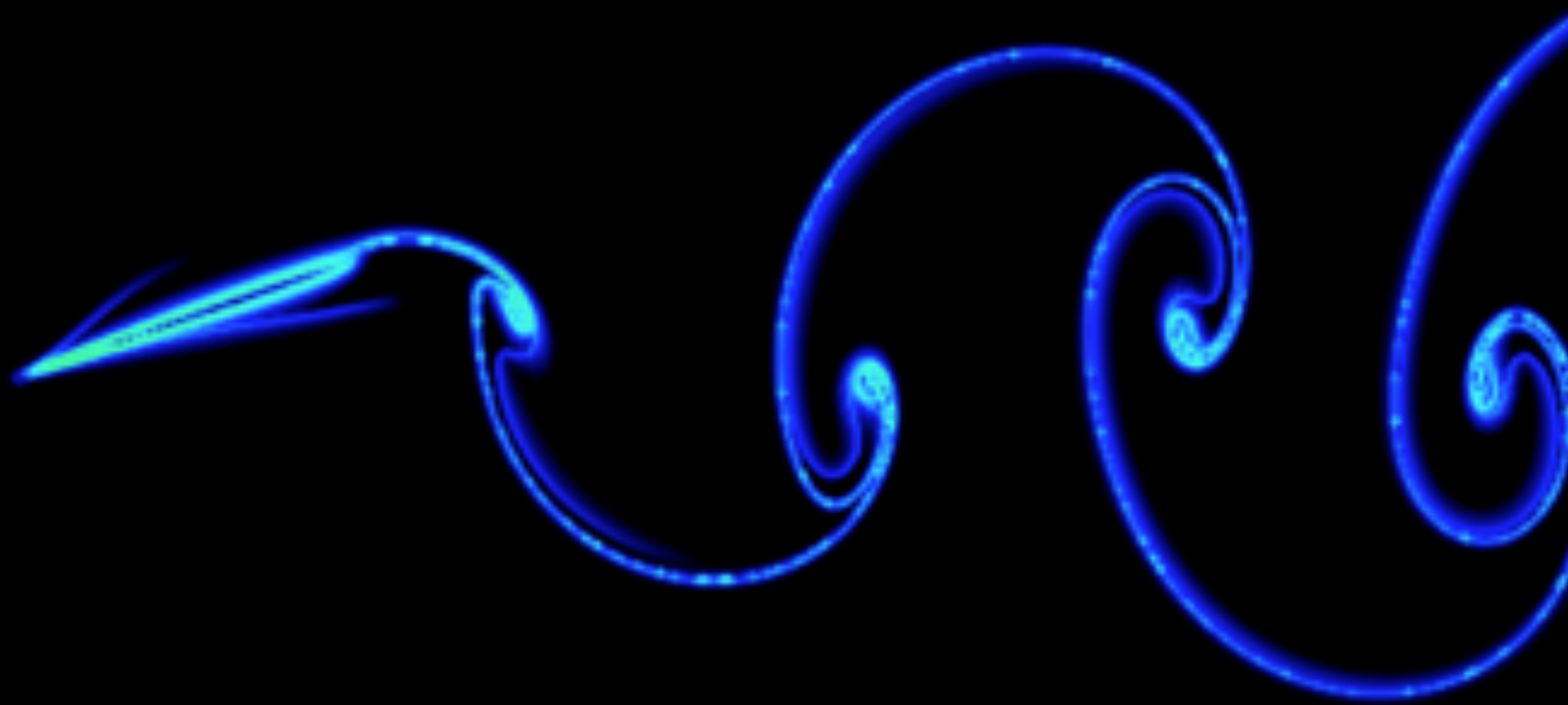
2D Incompressible Navier-Stokes:

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u}\cdot\nabla)\,\mathbf{u} = -\nabla p + \frac{1}{\mathrm{Re}}\nabla^2\mathbf{u} + \int_s \mathbf{f}\left(\xi(s,t)\right)\delta(\xi - \mathbf{x})ds$$

$$\nabla\cdot\mathbf{u} = 0$$

$$\mathbf{u}\left(\xi(s,t)\right) = \int_{\mathbf{x}} \mathbf{u}(\mathbf{x})\delta(\mathbf{x}-\xi)d\mathbf{x} = \mathbf{u}_B\left(\xi(s,t)\right)$$

Pitch



Immersed boundary method

Boundary forces computed as Lagrange-multipliers to enforce no slip

Taira & Colonius, 2007.
Colonius & Taira, 2008.

Dynamical Systems: Poincare and Geometry

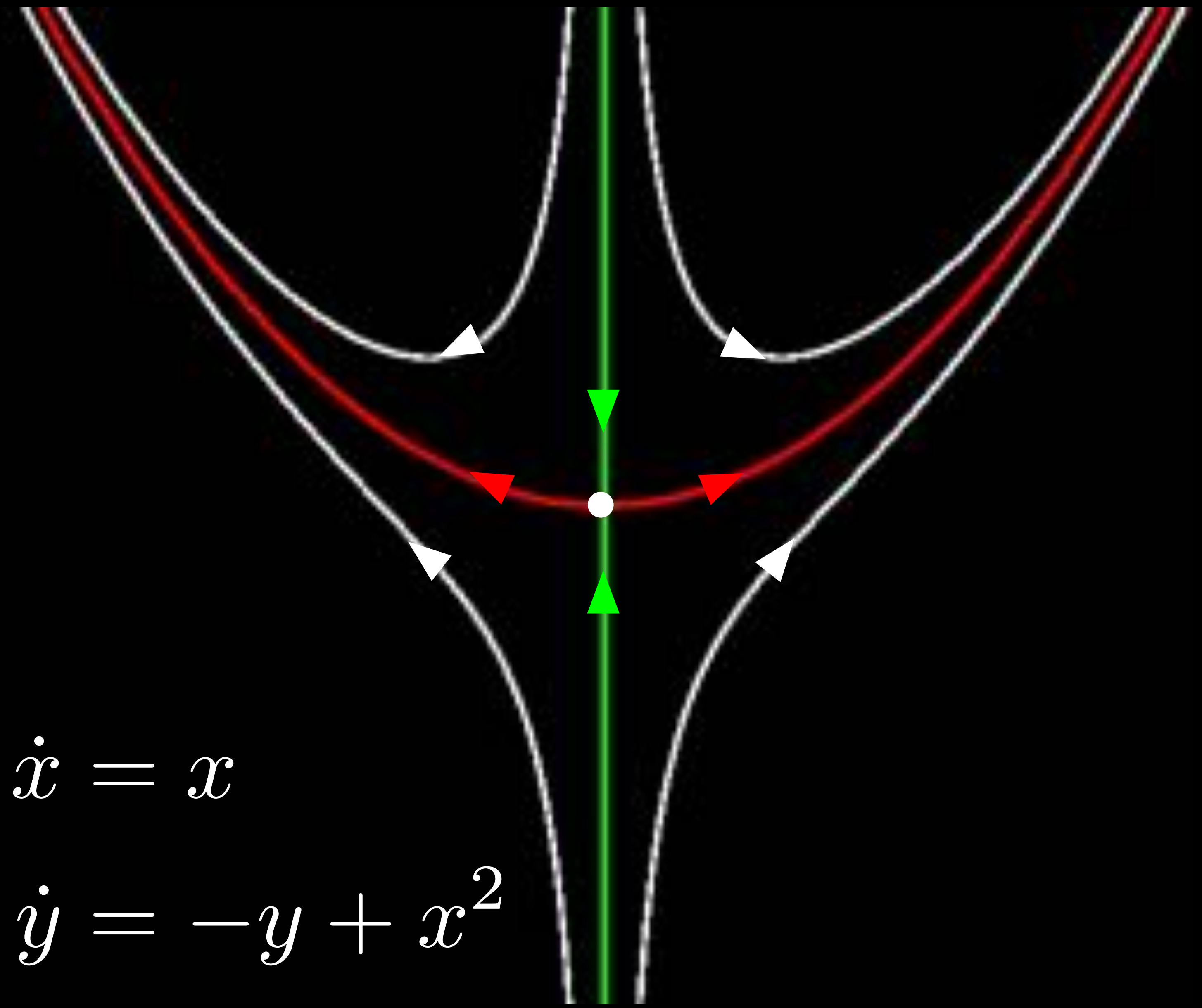
Dynamics

$$\frac{d}{dt}\mathbf{x} = \mathbf{f}(\mathbf{x}), \quad \Rightarrow \quad \mathbf{F}_t(\mathbf{x}(t_0)) = \mathbf{x}(t_0 + t) = \mathbf{x}(t_0) + \int_{t_0}^{t_0+t} \mathbf{f}(\mathbf{x}(\tau))\, d\tau.$$

$$\Rightarrow \quad \mathbf{x}_{k+1} = \mathbf{F}_t(\mathbf{x}_k),$$

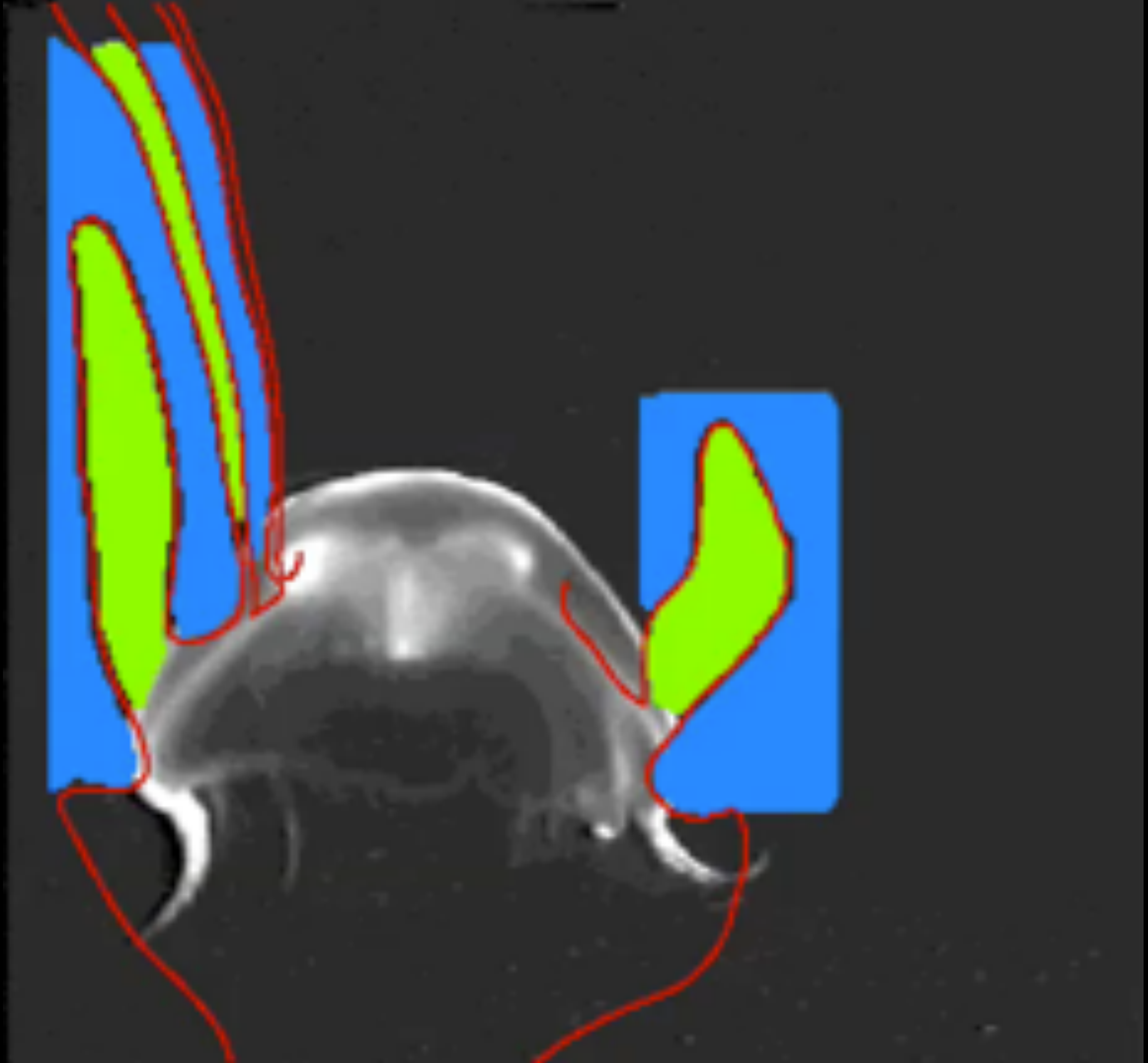
Discrete-time update

Haller, 2002;
Shadden *et al.*, 2005

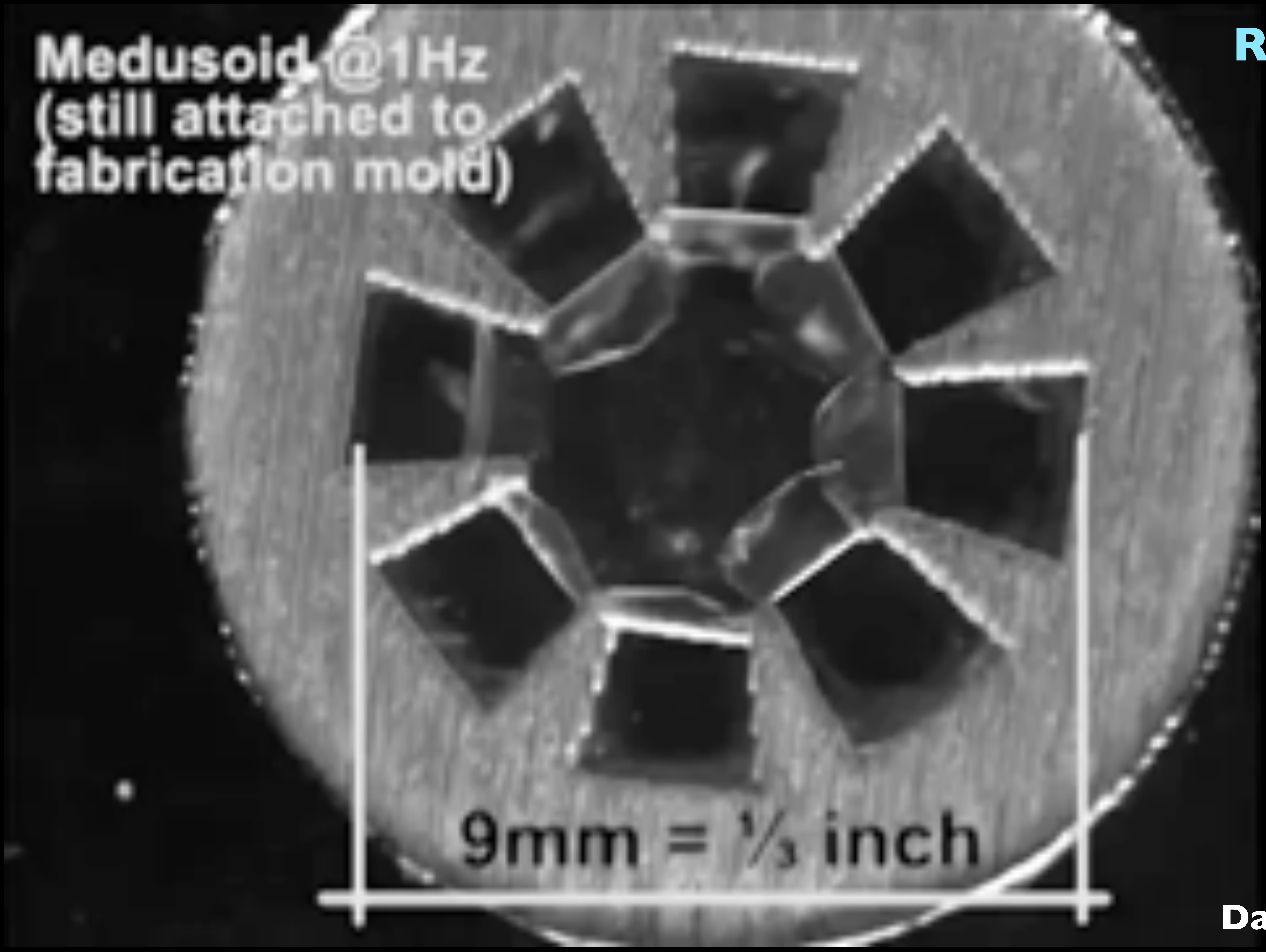


Finite-time Lyapunov exponents (FTLE)

How Jellyfish Eat



Shadden, Dabiri, and Marsden, 2006

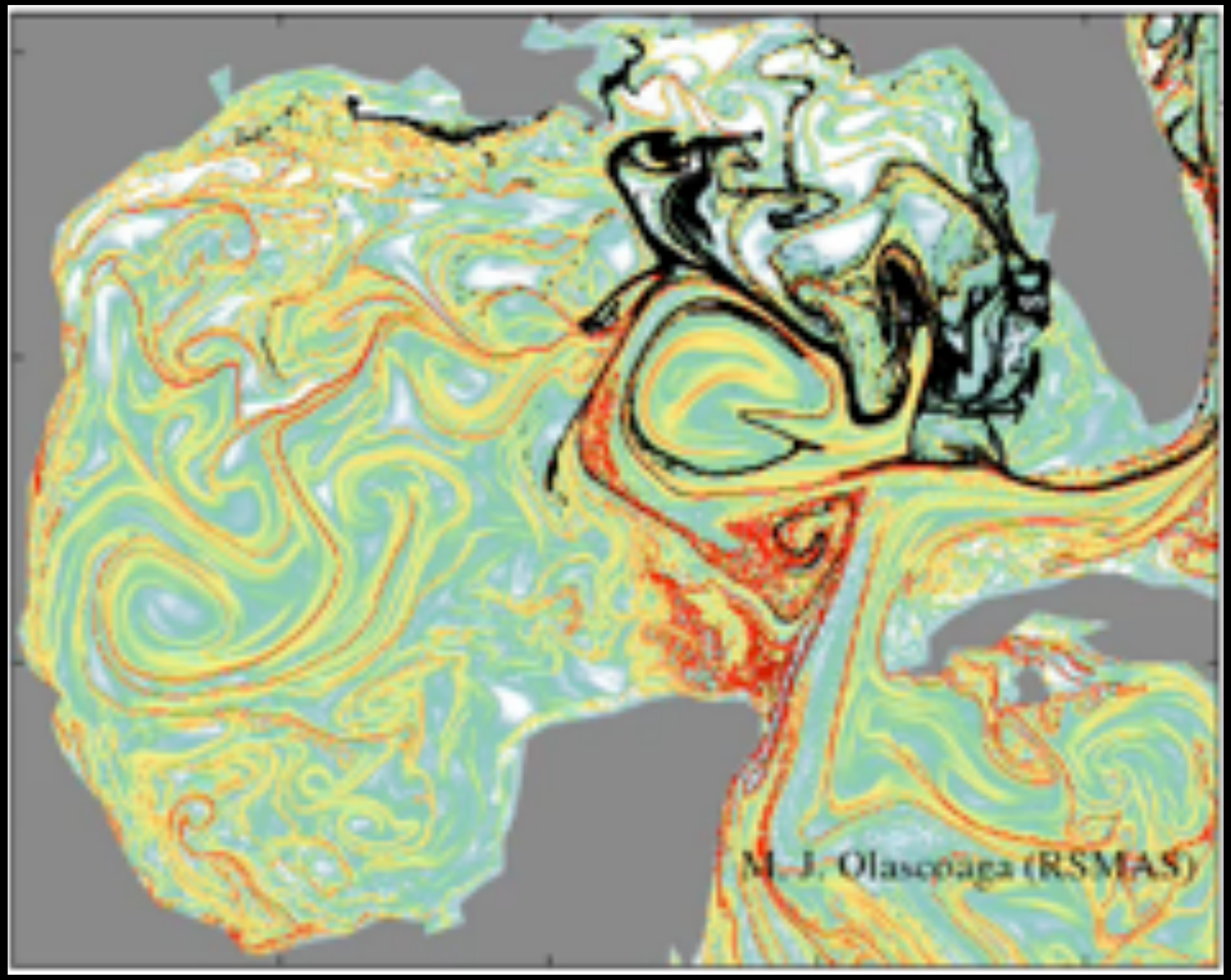


Robotic Jellyfish!

Dabiri & Parker, 2012

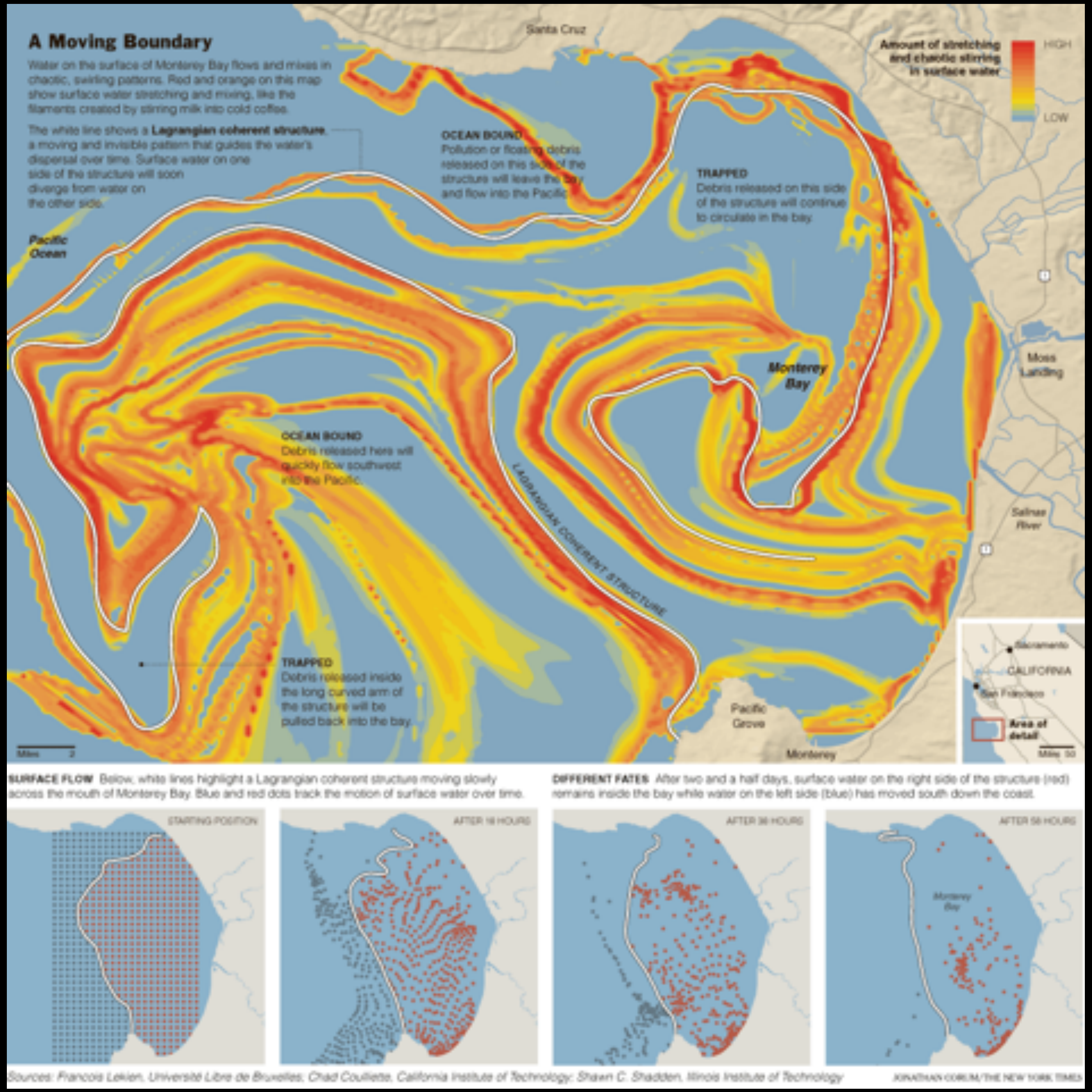
Contaminate Release in the Ocean

Olascoaga, NOAA 2010



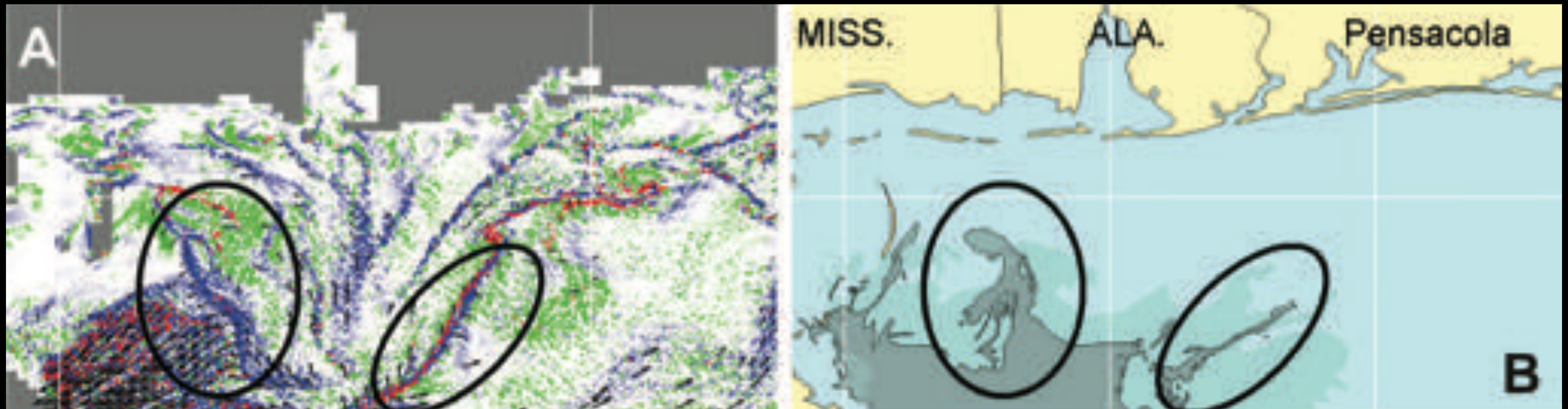
Gulf Oil Spill

Monterey Bay

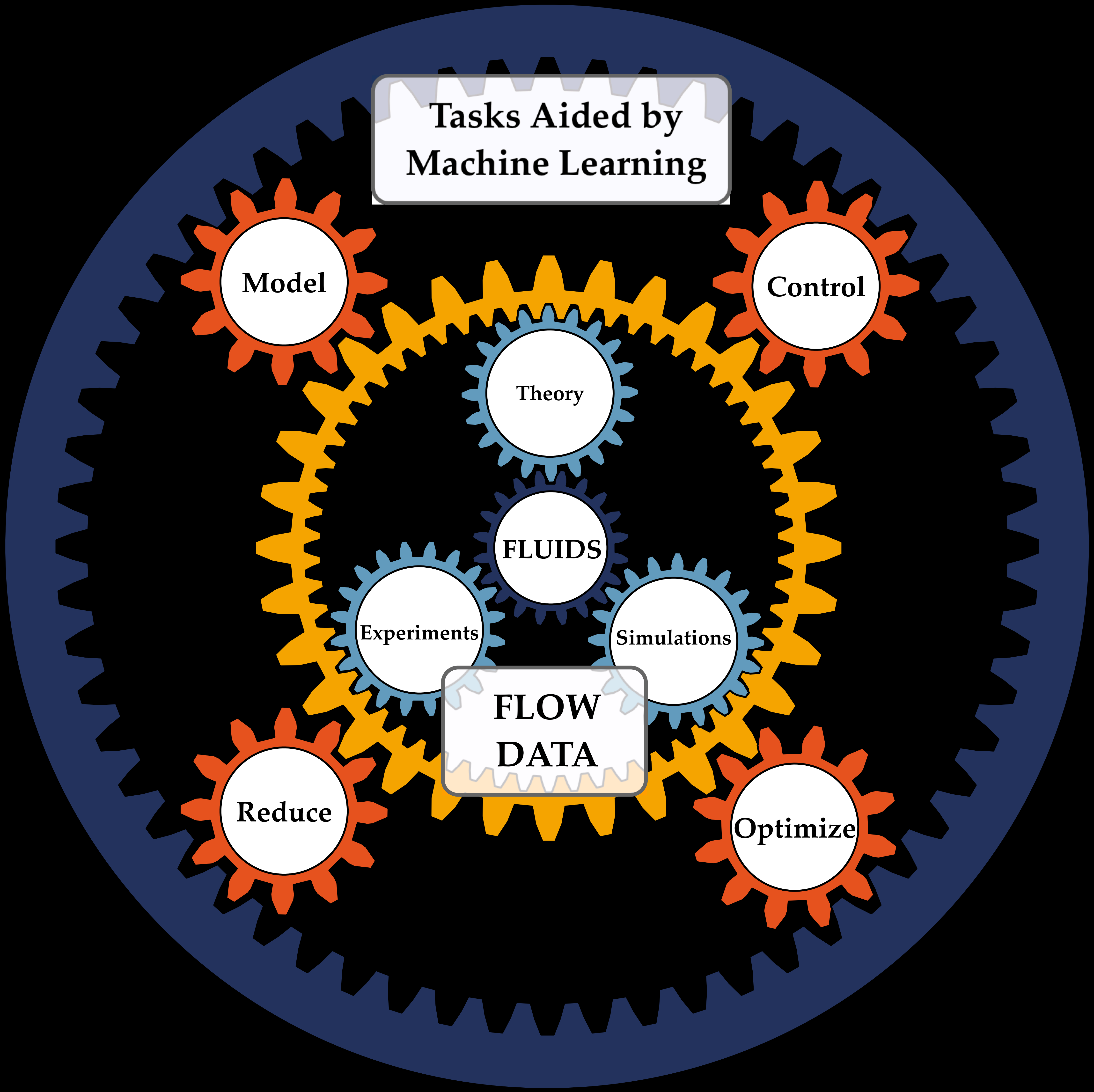


Lekien, Coulliette, Shadden
J. Marsden & N. Leonard, 2005

Mezic, *et al*, Science 2010.




du Toit,
2010



Machine Learning for Fluid Mechanics

Steven L. Brunton,[1] Bernd R. Noack,[2] and Petros Koumoutsakos[3],[4]

[1]Mechanical Engineering, University of Washington, Seattle, WA, USA, 98115; email: sbrunton@uw.edu
[2] Laboratoire d'Informatique pour la Mécanique et les Sciences de l'Ingénieur, LIMSI-CNRS, Rue John von Neumann, Campus Universitaire d'Orsay, Bât 508, F-91403 Orsay, France
[3] Computational Science and Engineering Laboratory, ETH Zurich, CH-8092, Switzerland
[4] Collegium Helveticum, Zurich, CH-8092, Switzerland

Xxxx. Xxx. Xxx. Xxx. YYYY. AA:1–31

https://doi.org/10.1146/((please add article doi))

Keywords

machine learning, data-driven modeling, optimization, control

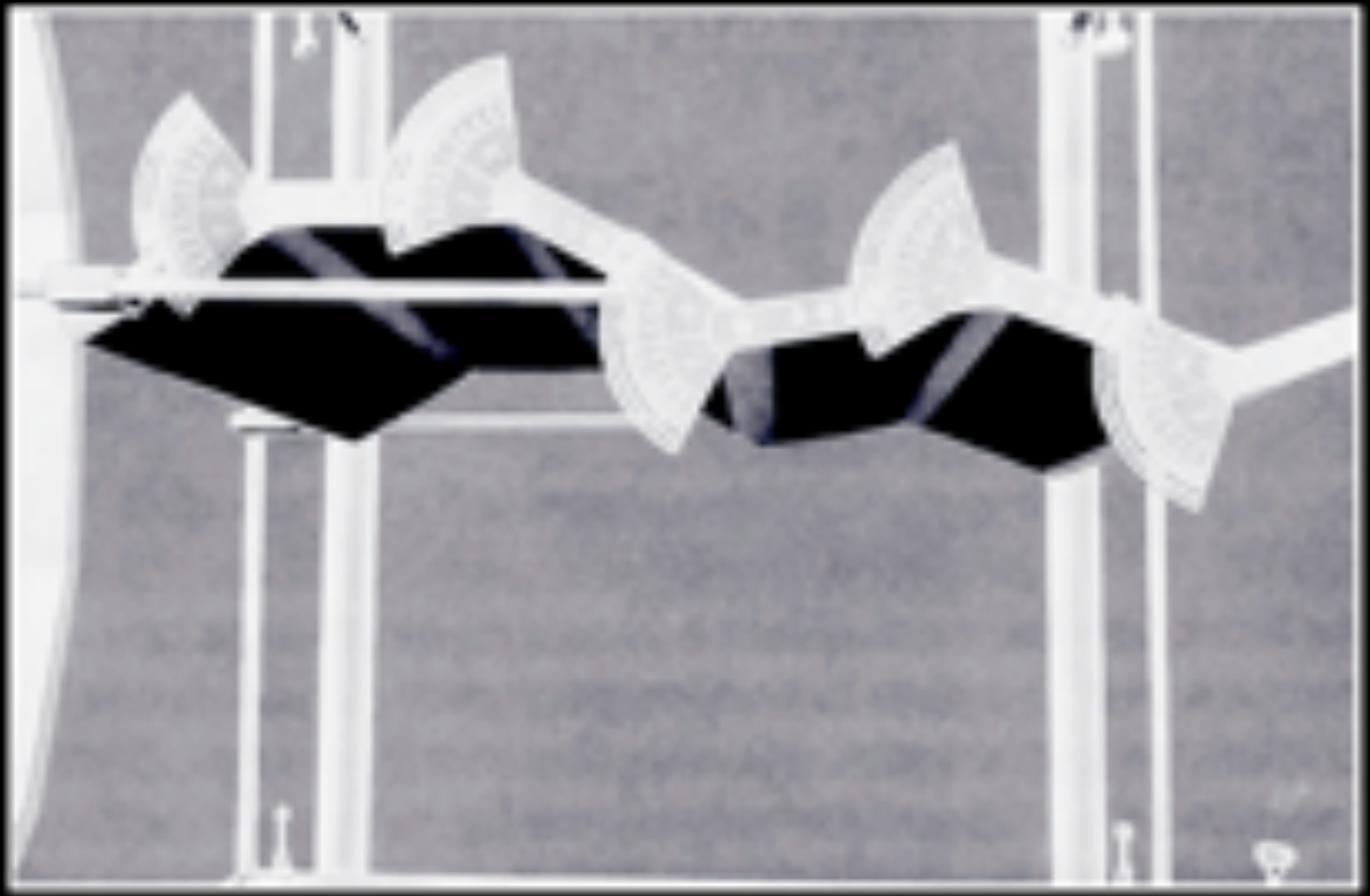
Abstract

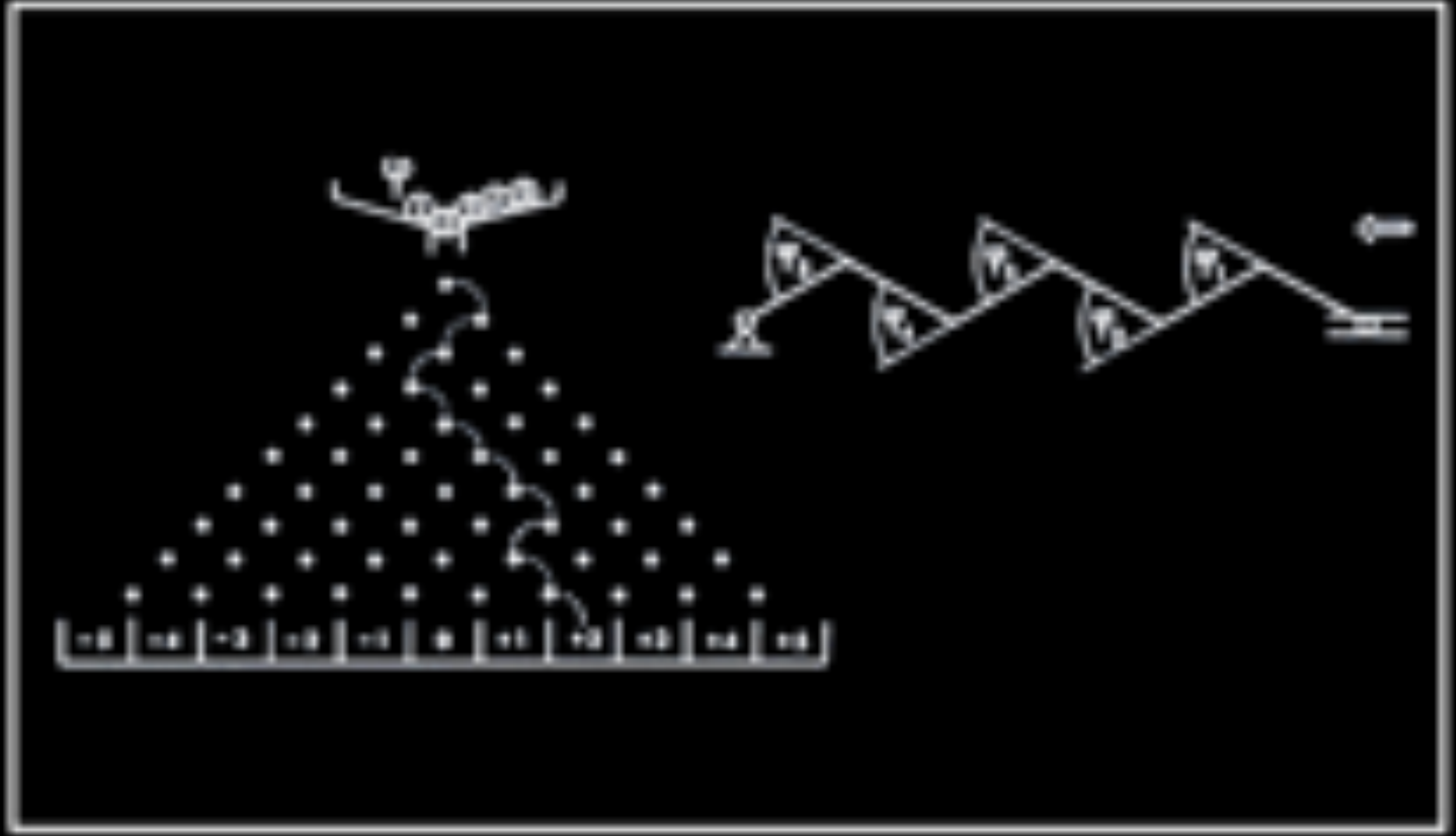
The field of fluid mechanics is rapidly advancing, driven by unprecedented volumes of data from experiments, field measurements, and large-scale simulations at multiple spatiotemporal scales. Machine learning presents us with a wealth of techniques to extract information from data that can be translated into knowledge about the underlying fluid mechanics. Moreover, machine learning algorithms can augment domain knowledge and automate tasks related to flow control and optimization. This article presents an overview of past history, current developments, and emerging opportunities of machine learning for fluid mechanics. We outline fundamental machine learning methodologies and discuss their uses for understanding, modeling, optimizing, and controlling fluid flows. The strengths and limitations of these methods are addressed from the perspective of scientific inquiry that links data with modeling, experiments, and simulations. Machine learning provides a powerful information processing framework that can augment, and possibly even transform, current lines of fluid mechanics research and industrial applications.

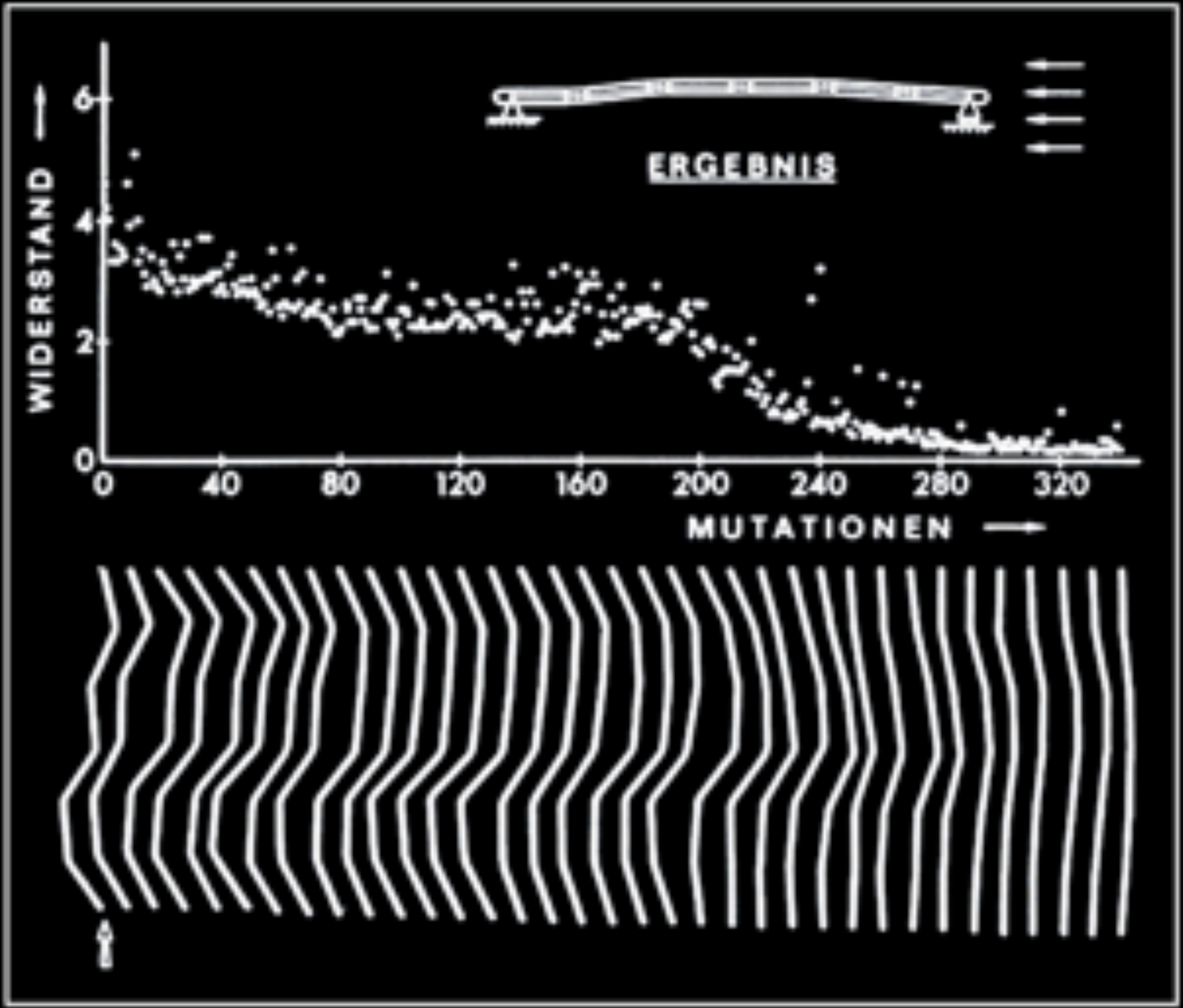
HISTORY

Reichenberg, 1960s-1970s
Schweifel, 1970s

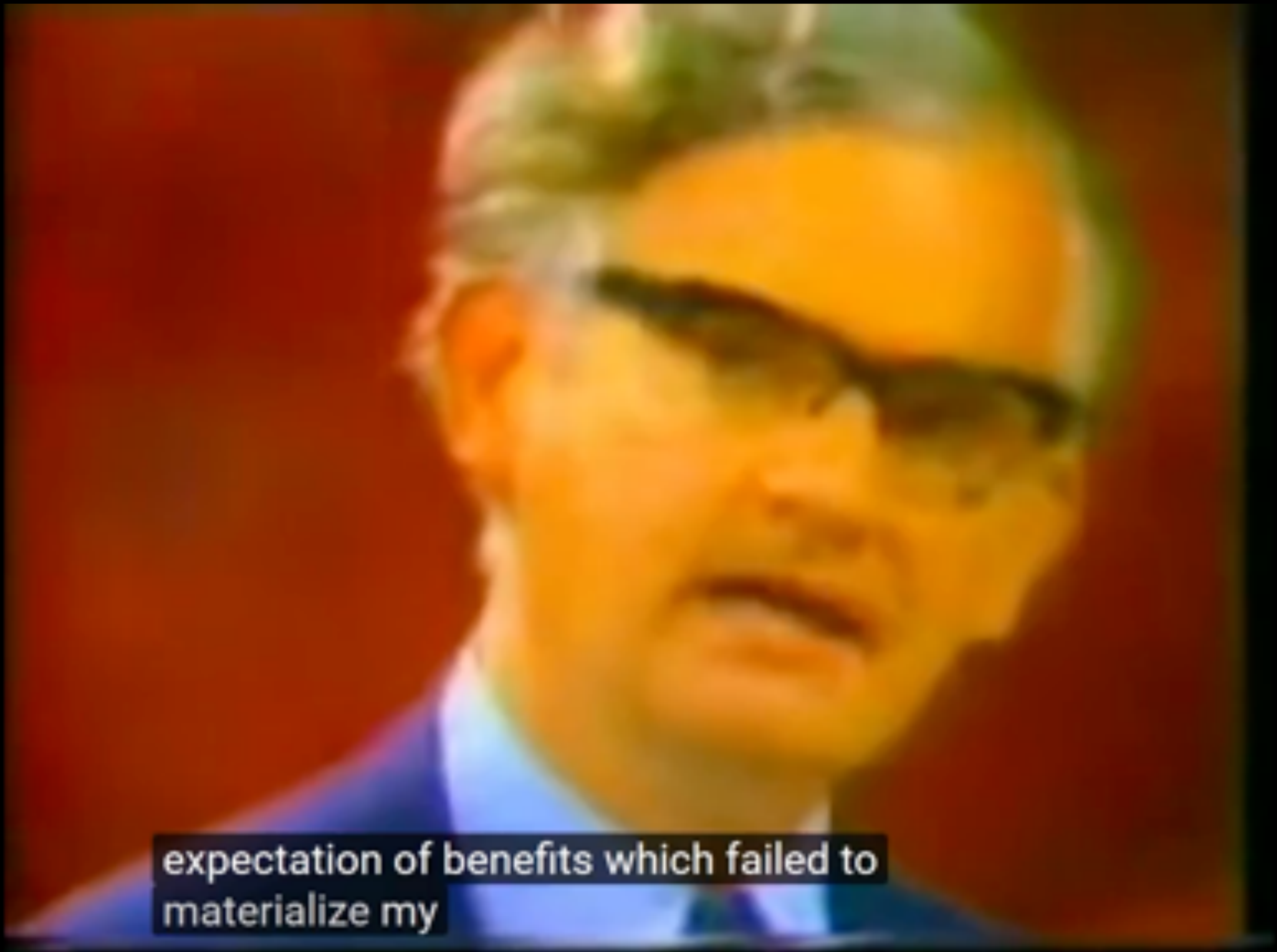
SLB, Noack, Koumoutsakos,
Ann. Rev. Fluid Mech. 2019







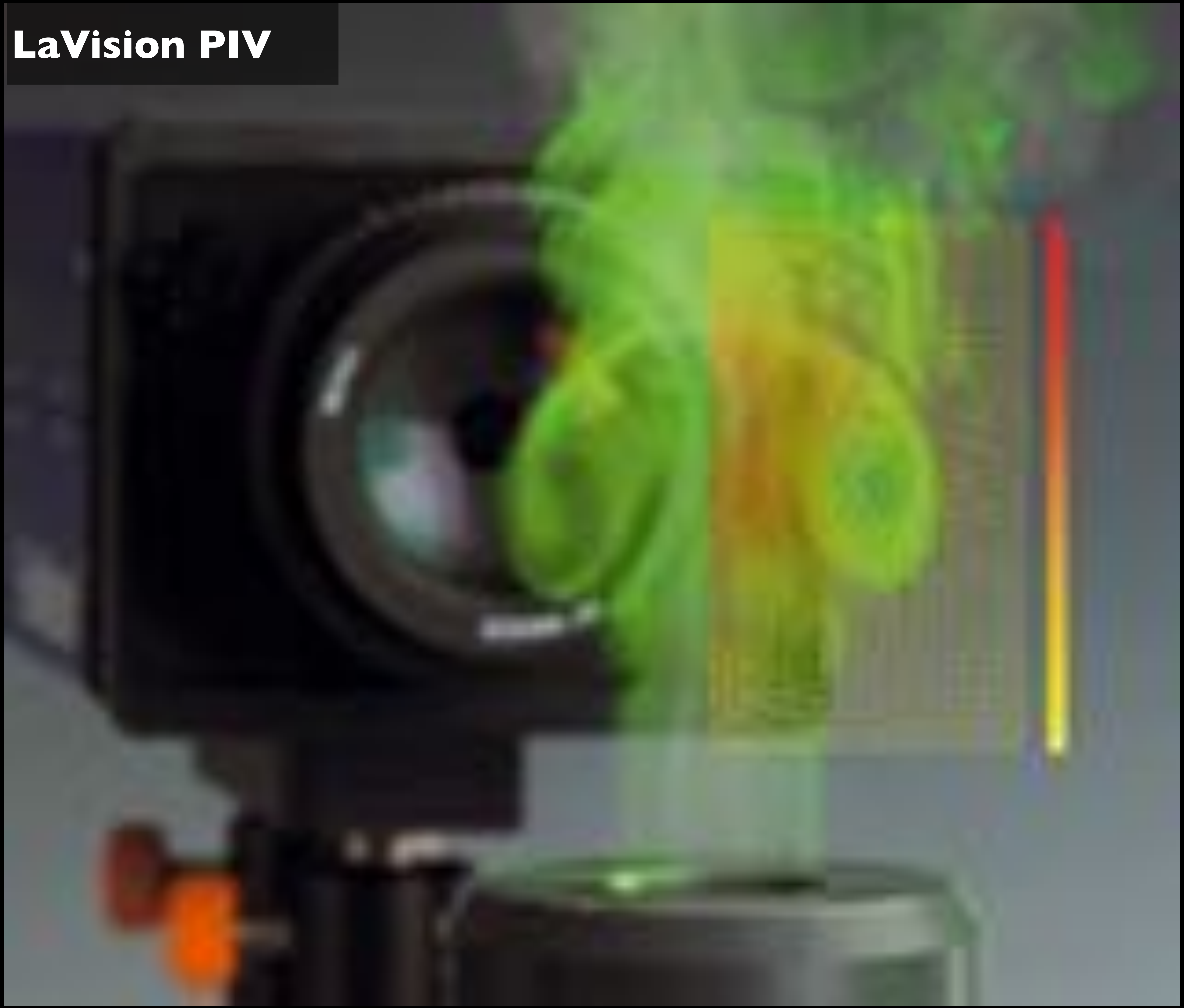
Sir Lighthill and the AI Winter (1974)



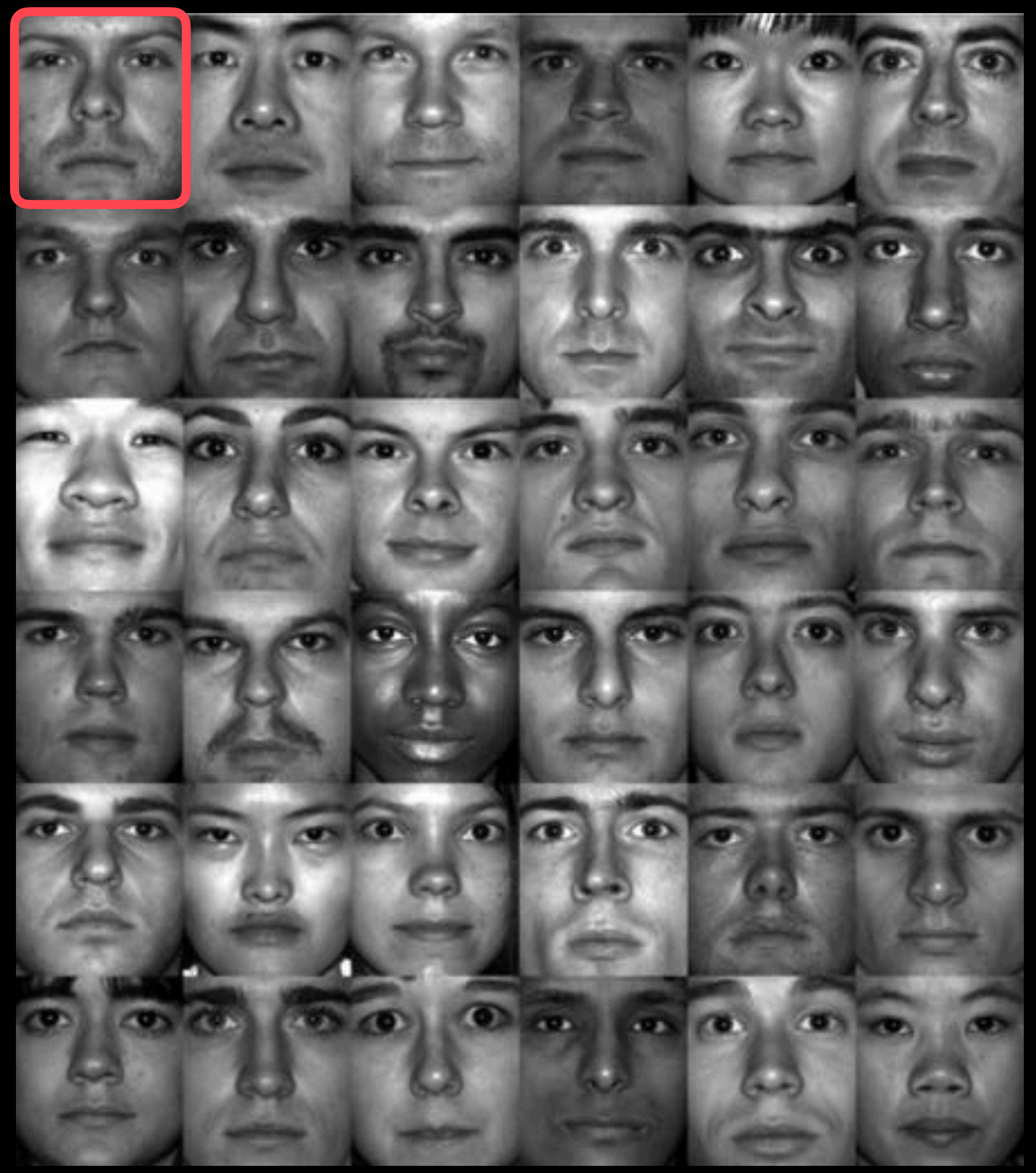
https://www.youtube.com/watch?v=ug0oZAwjC6g

EXPERIMENTAL MEASUREMENTS

Particle Image Velocimetry (PIV)

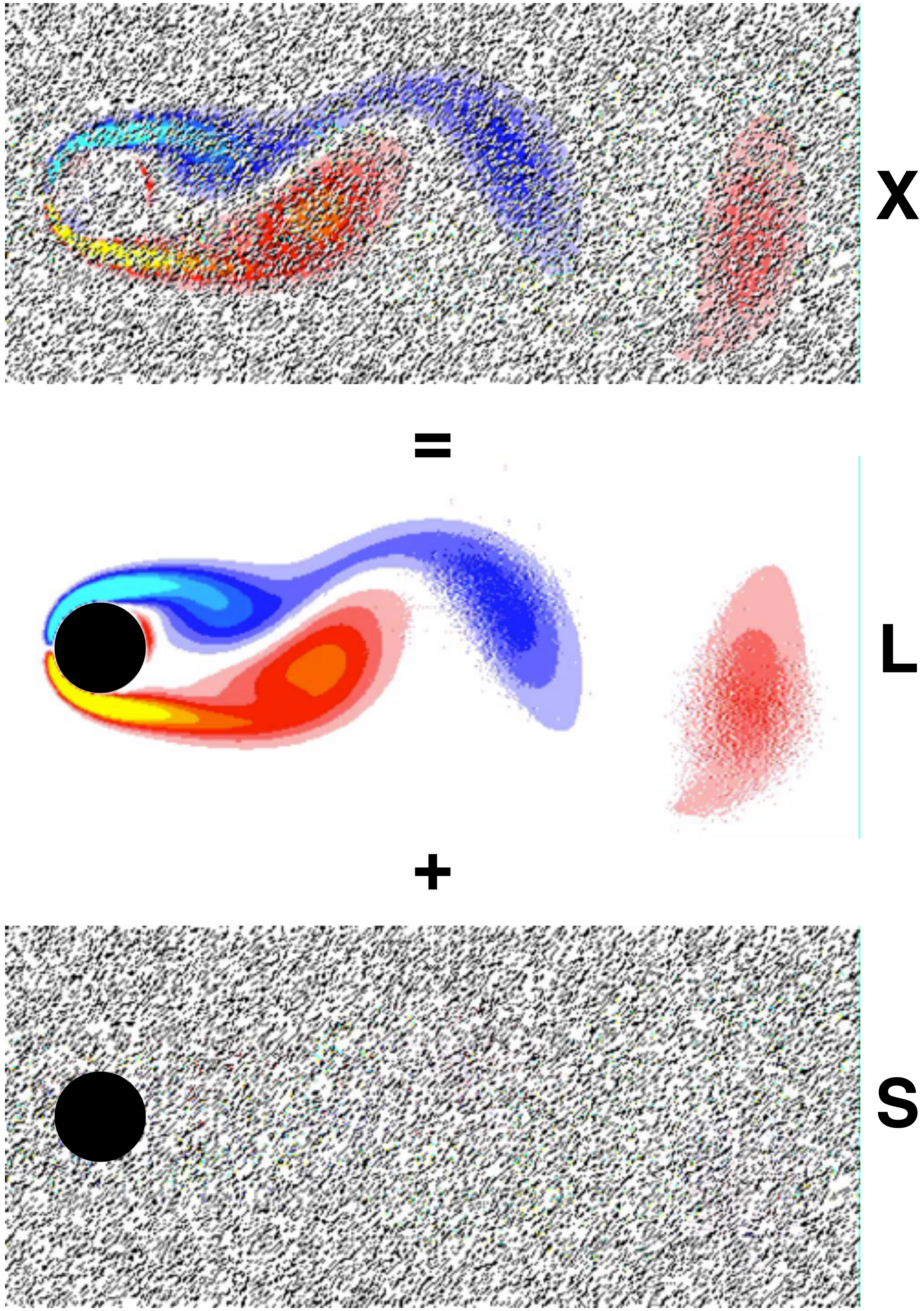


ROBUST STATISTICS (RPCA)



Candes *et al.*, *J. ACM*, 2011

Robust Principal Component Analysis (RPCA)



$$\mathbf{X} = \mathbf{L} + \mathbf{S}.$$

$$\min_{\mathbf{L},\mathbf{S}} \operatorname{rank}(\mathbf{L}) + \|\mathbf{S}\|_0$$

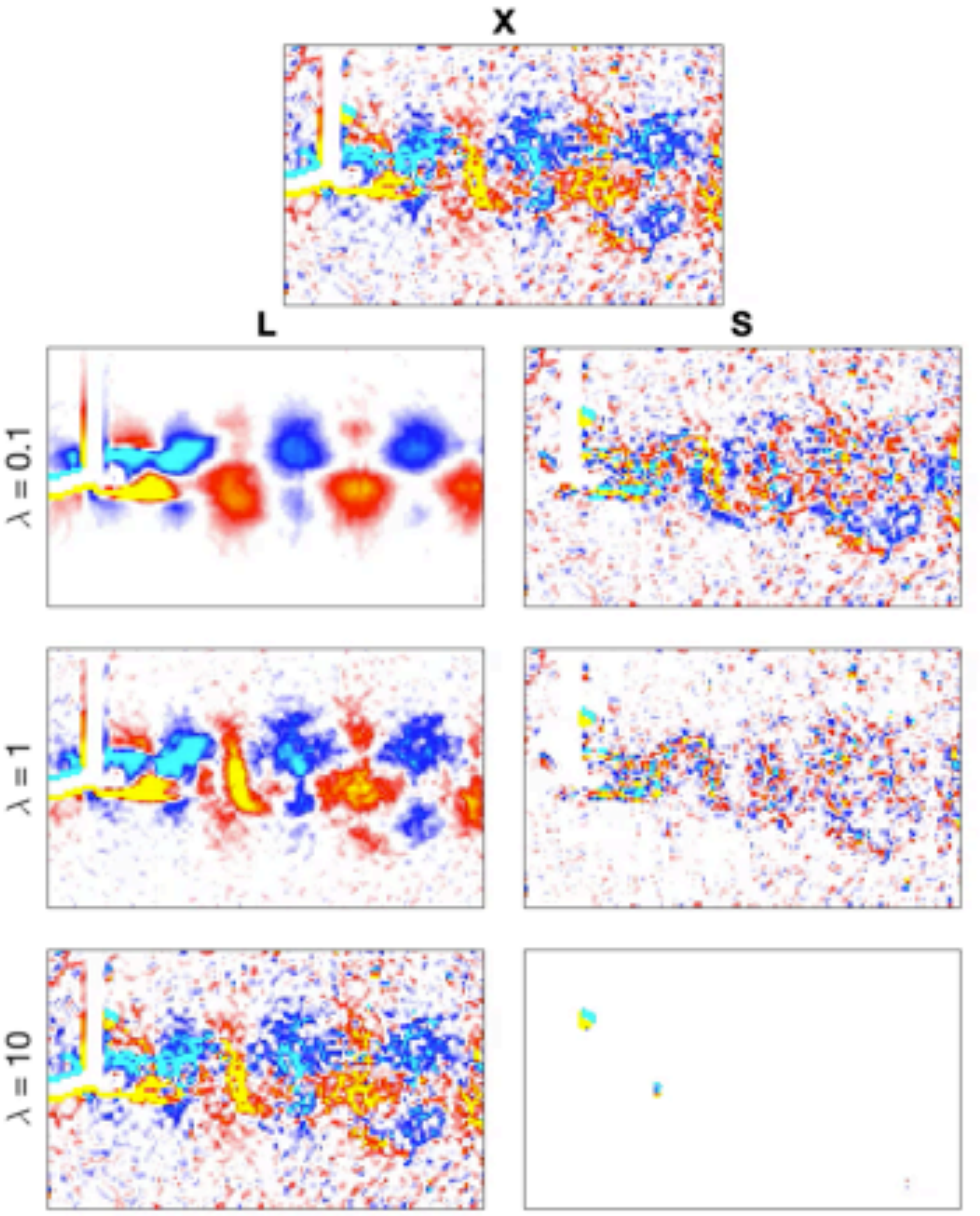
$$\text{subject to } \mathbf{L} + \mathbf{S} = \mathbf{X}.$$

$$\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda_0 \|\mathbf{S}\|_1$$

$$\text{subject to } \mathbf{L} + \mathbf{S} = \mathbf{X}.$$

Candes *et al.*, *J. ACM*, 2011
Scherl *et al.*, arXiv:1905.07062, 2019

Robust Principal Component Analysis (RPCA)



$$\mathbf{X} = \mathbf{L} + \mathbf{S}.$$

$$\min_{\mathbf{L},\mathbf{S}} \operatorname{rank}(\mathbf{L}) + \|\mathbf{S}\|_0$$

$$\text{subject to } \mathbf{L} + \mathbf{S} = \mathbf{X}.$$

$$\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda_0 \|\mathbf{S}\|_1$$

$$\text{subject to } \mathbf{L} + \mathbf{S} = \mathbf{X}.$$

Candes *et al.*, *J. ACM*, 2011
Scherl *et al.*, arXiv:1905.07062, 2019

SUPER RESOLUTION

SUPER RESOLUTION

Super-resolution reconstruction with machine learning 3

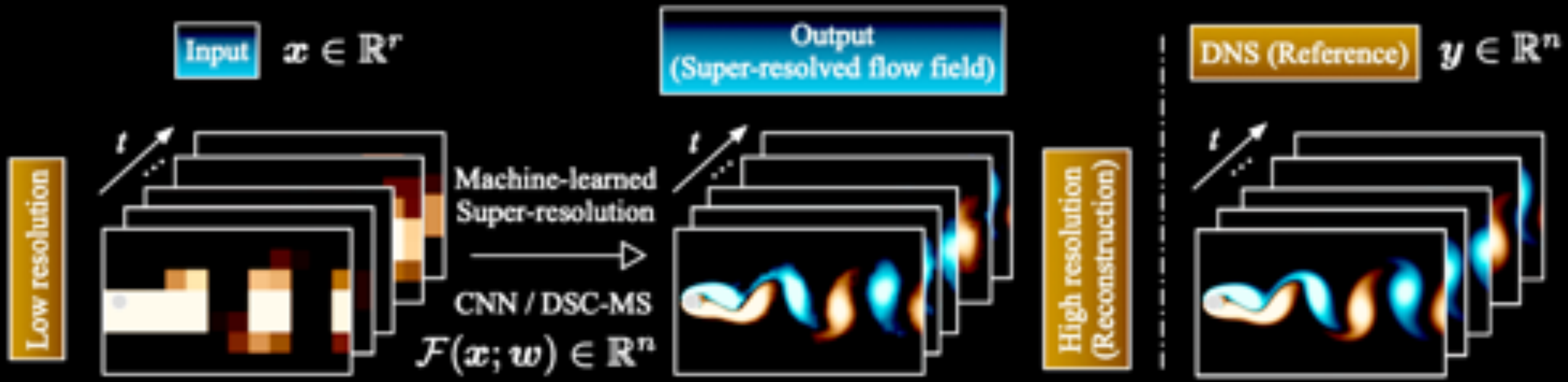
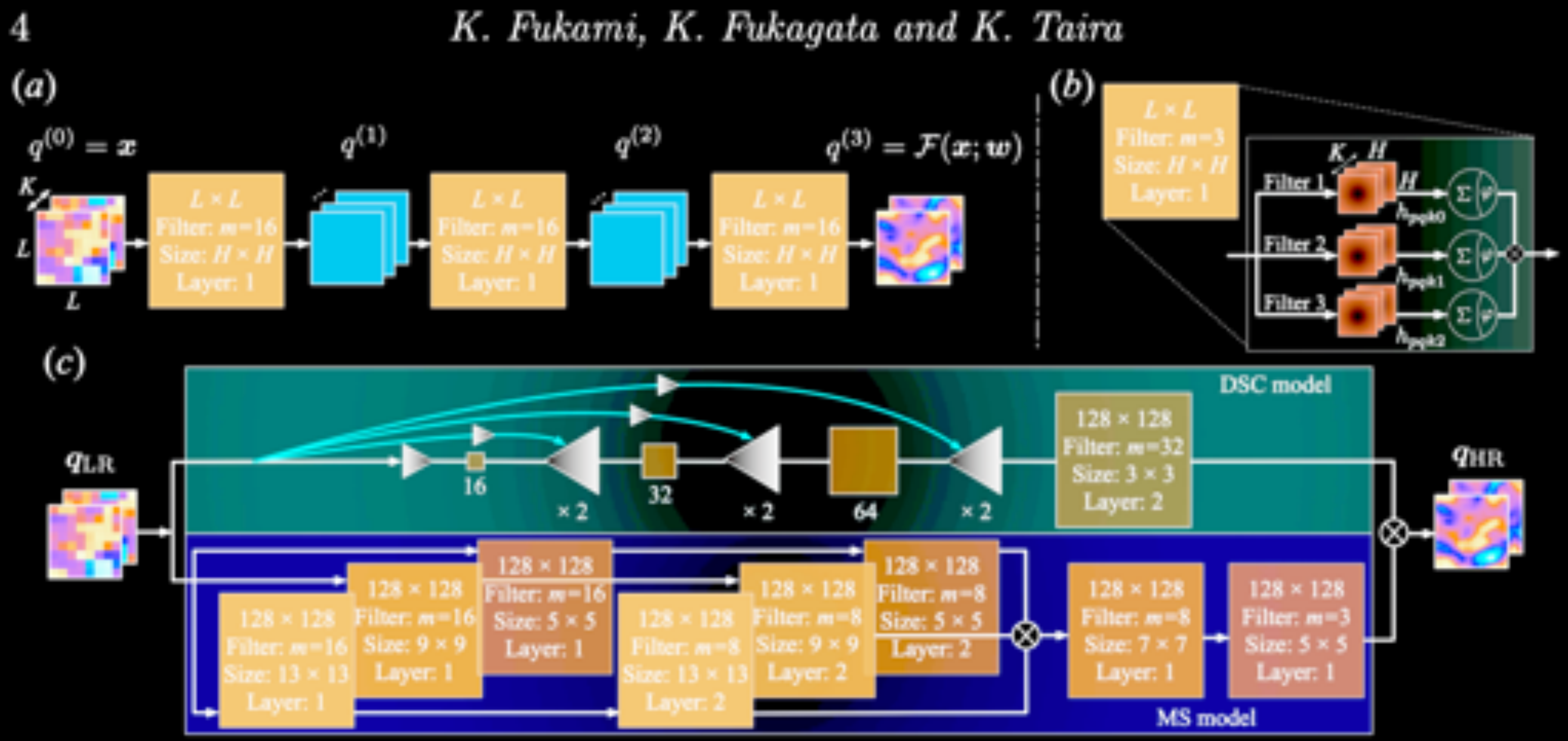


FIGURE 1. An overview of machine-learned super-resolution analysis for cylinder flow.

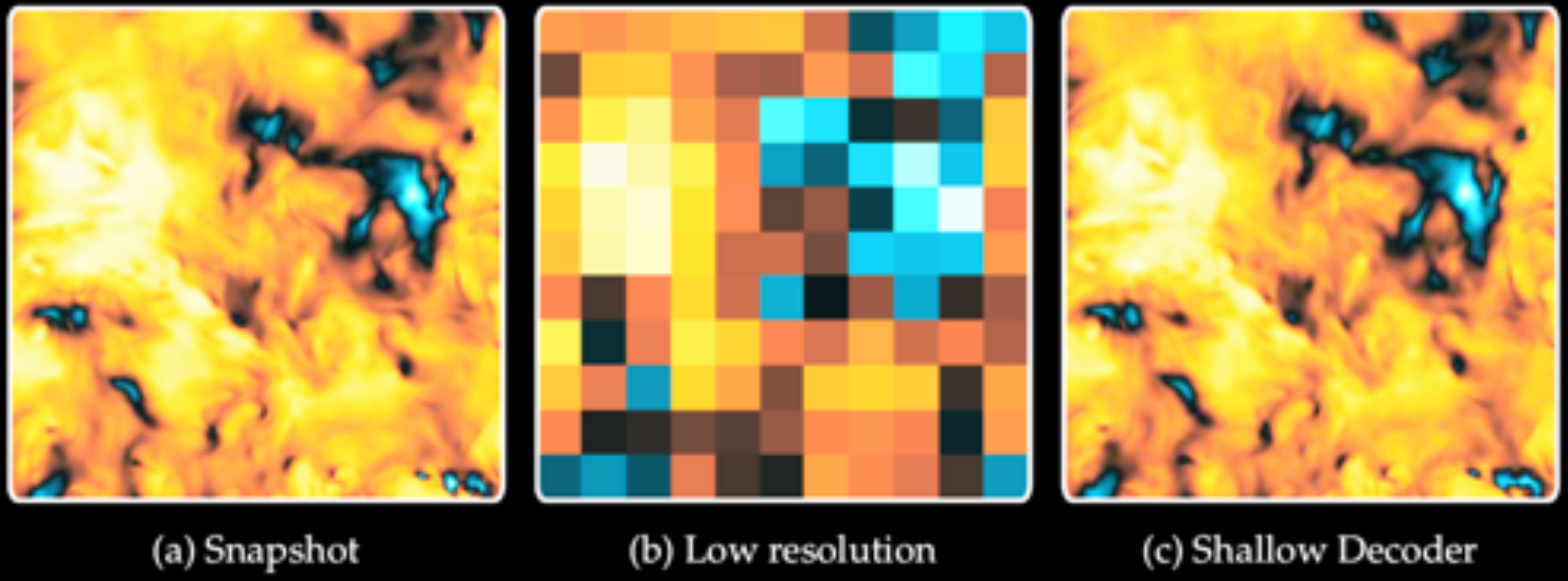
Fukami, Fukagata, Taira, *JFM*, 2019

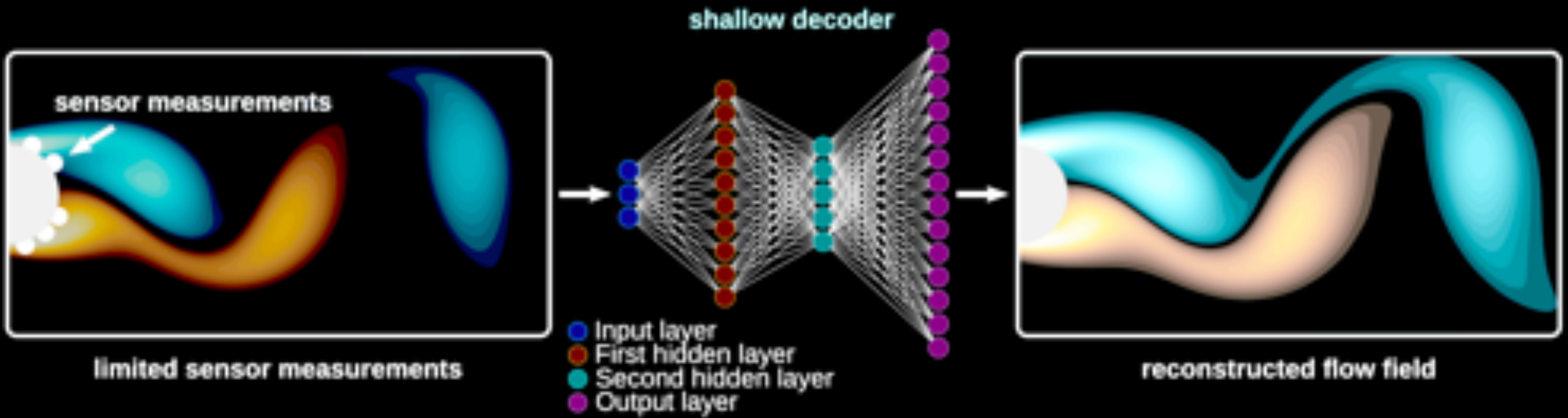
SUPER RESOLUTION



Fukami, Fukagata, Taira, *JFM*, 2019

SUPER RESOLUTION

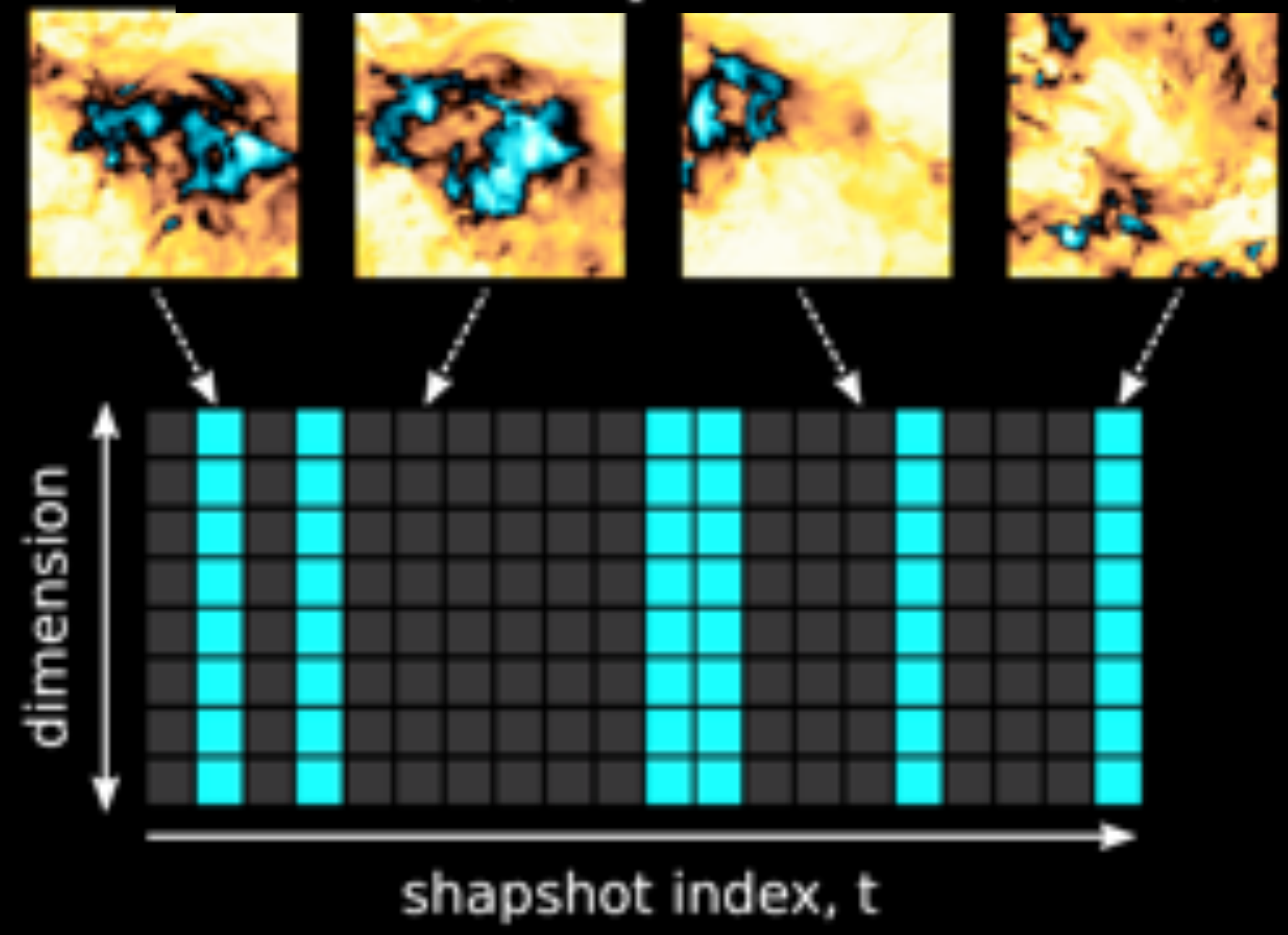




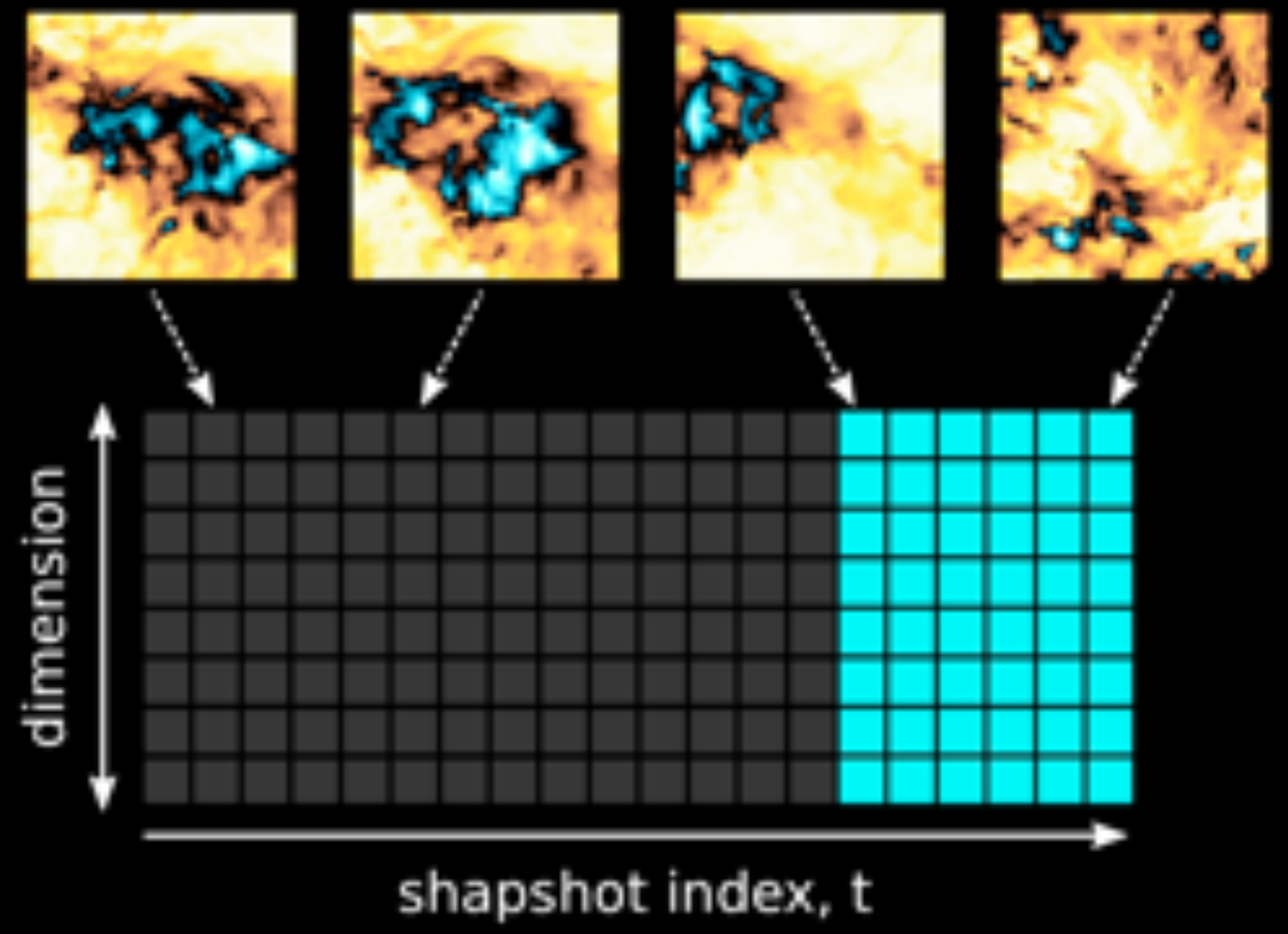
Erichson et al, *arXiv:1902.07358*, 2019

SUPER RESOLUTION

(a) Snapshot (b) Low resolution (c) Shallow Decoder



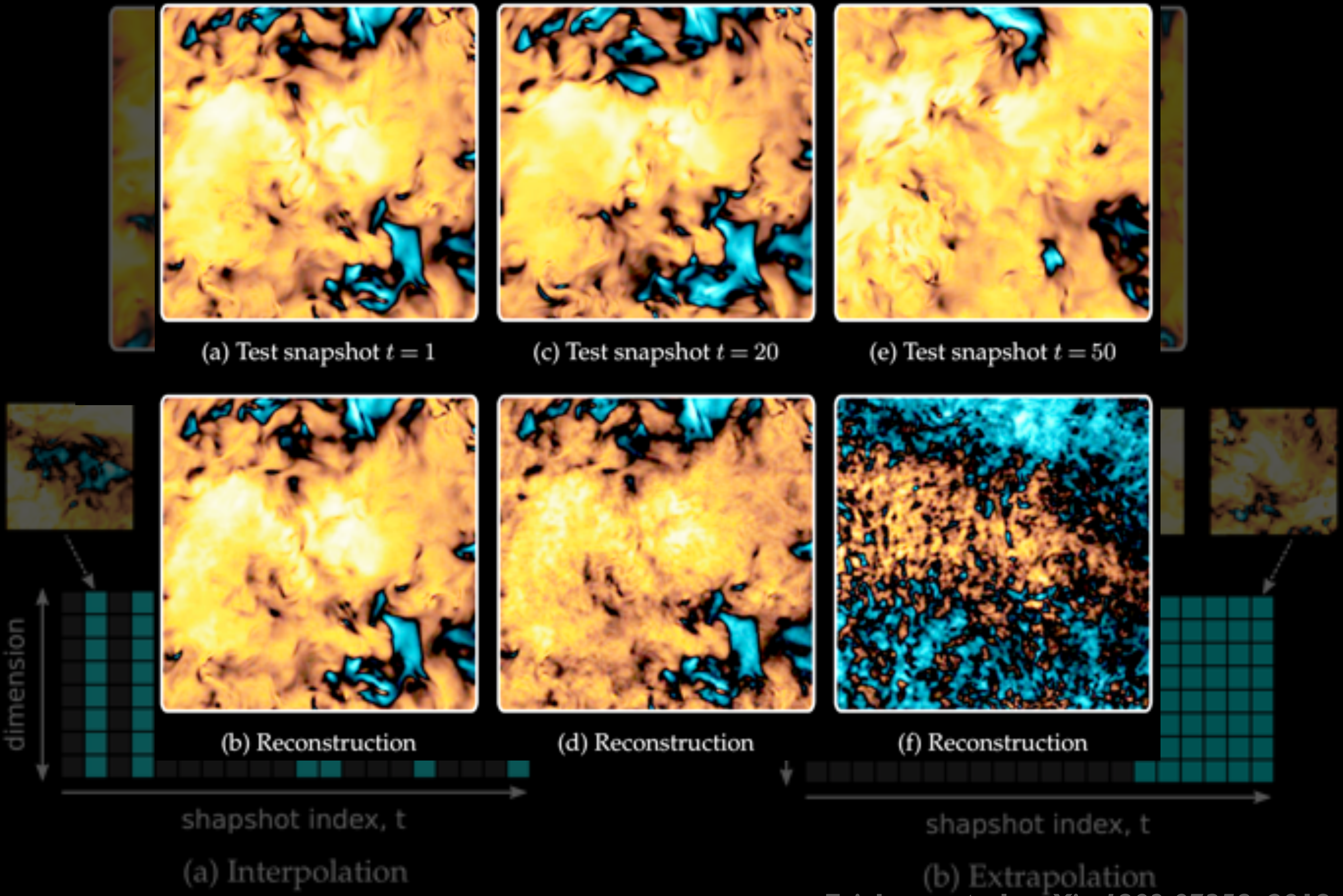
(a) Interpolation



(b) Extrapolation

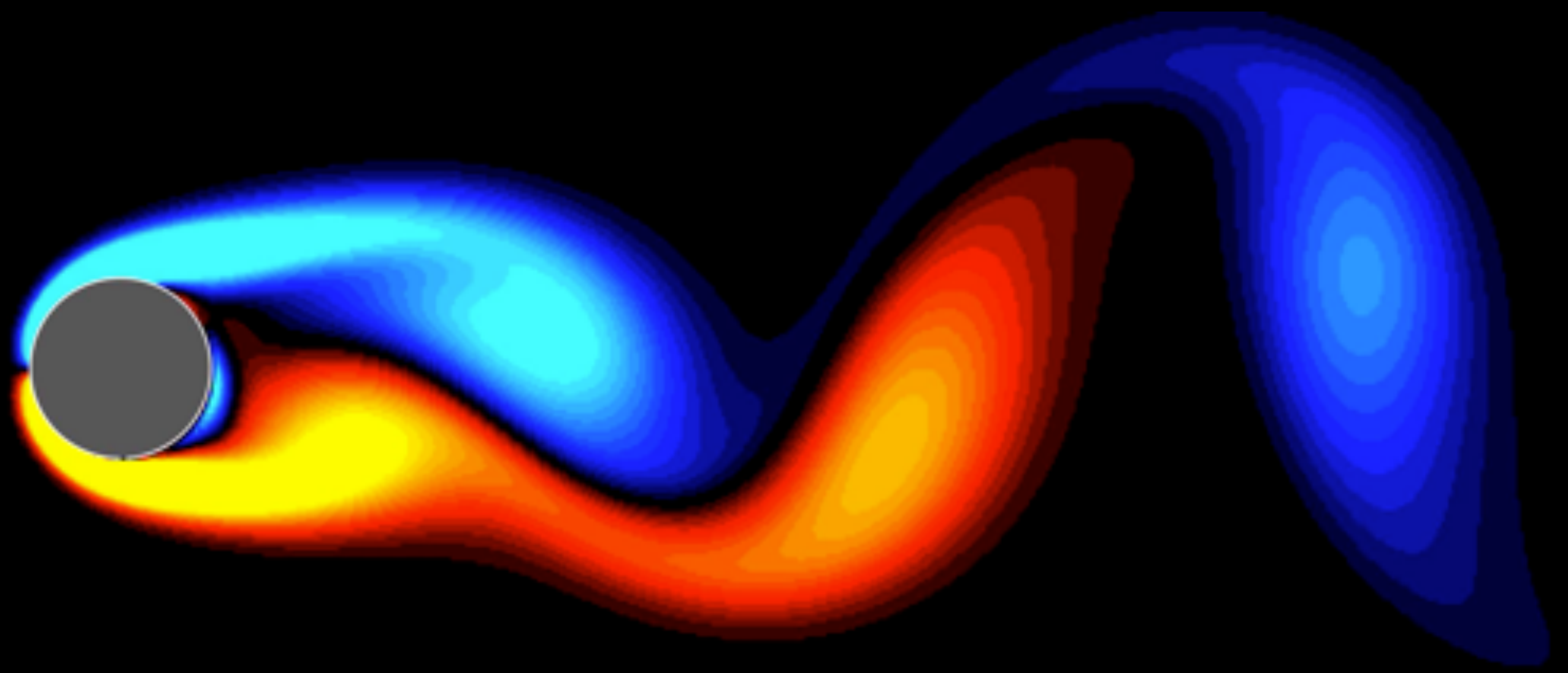
Erichson et al, *arXiv:1902.07358*, 2019

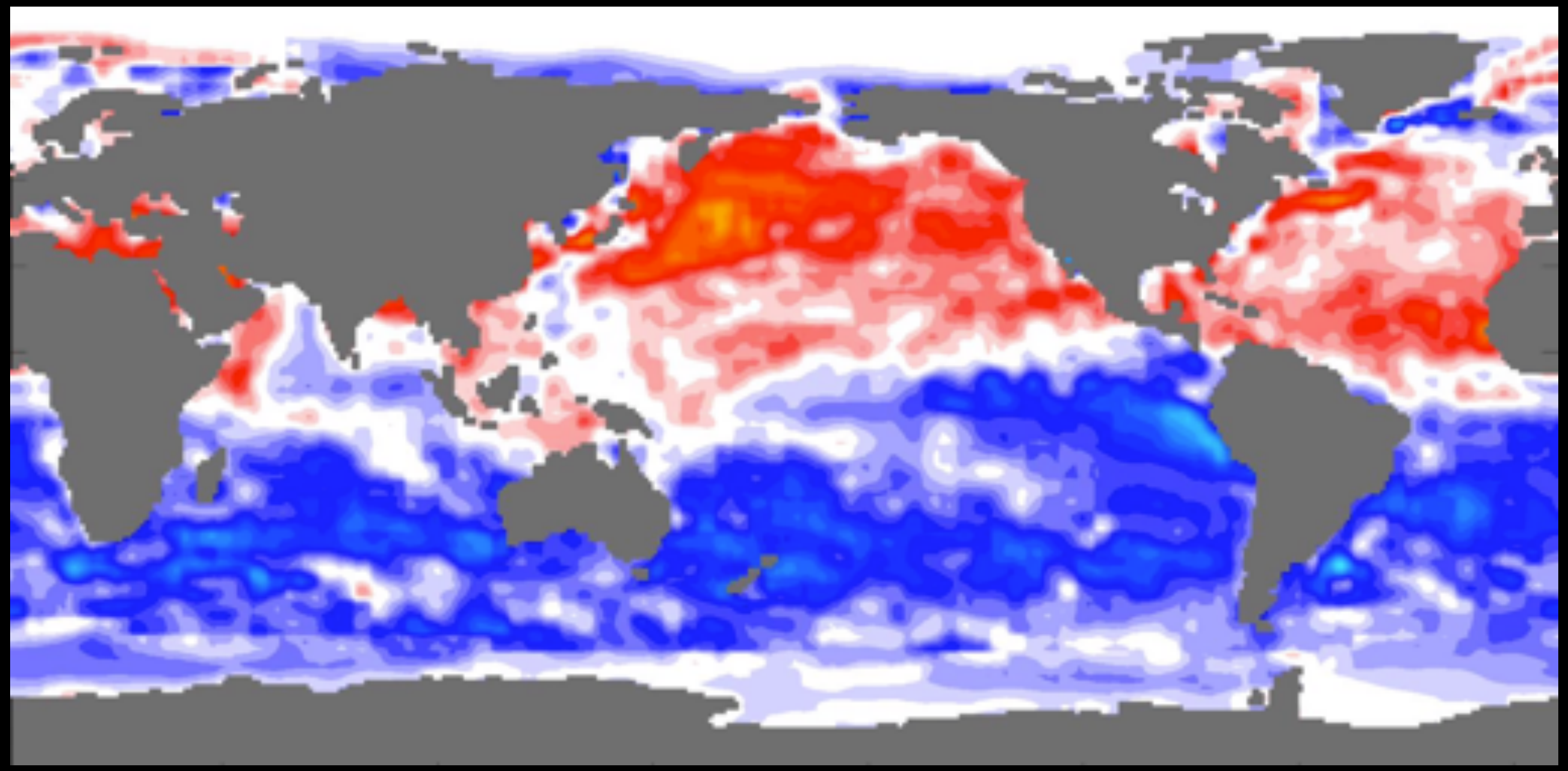
SUPER RESOLUTION

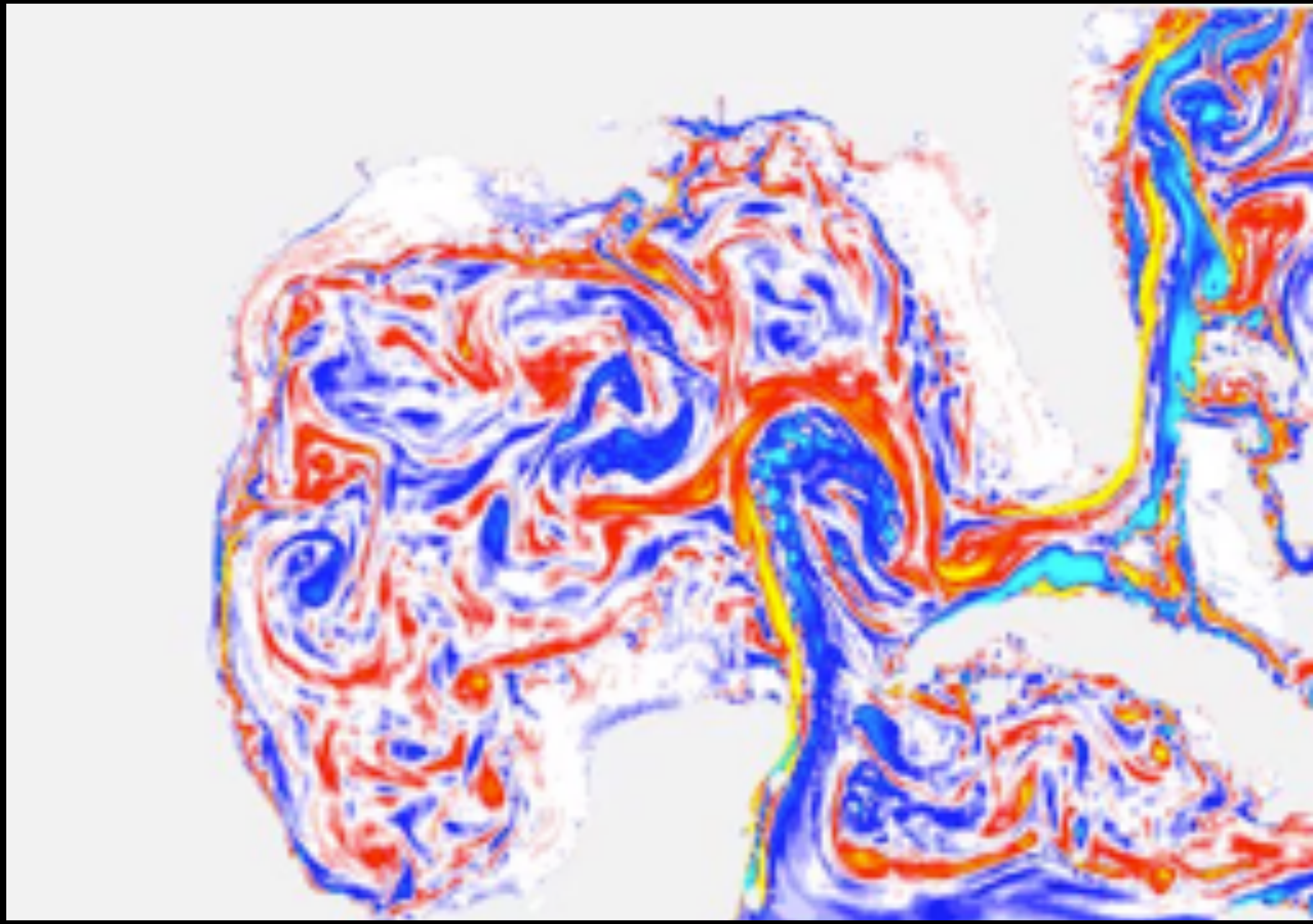


Erichson et al, *arXiv:1902.07358*, 2019

STATISTICAL STATIONARITY

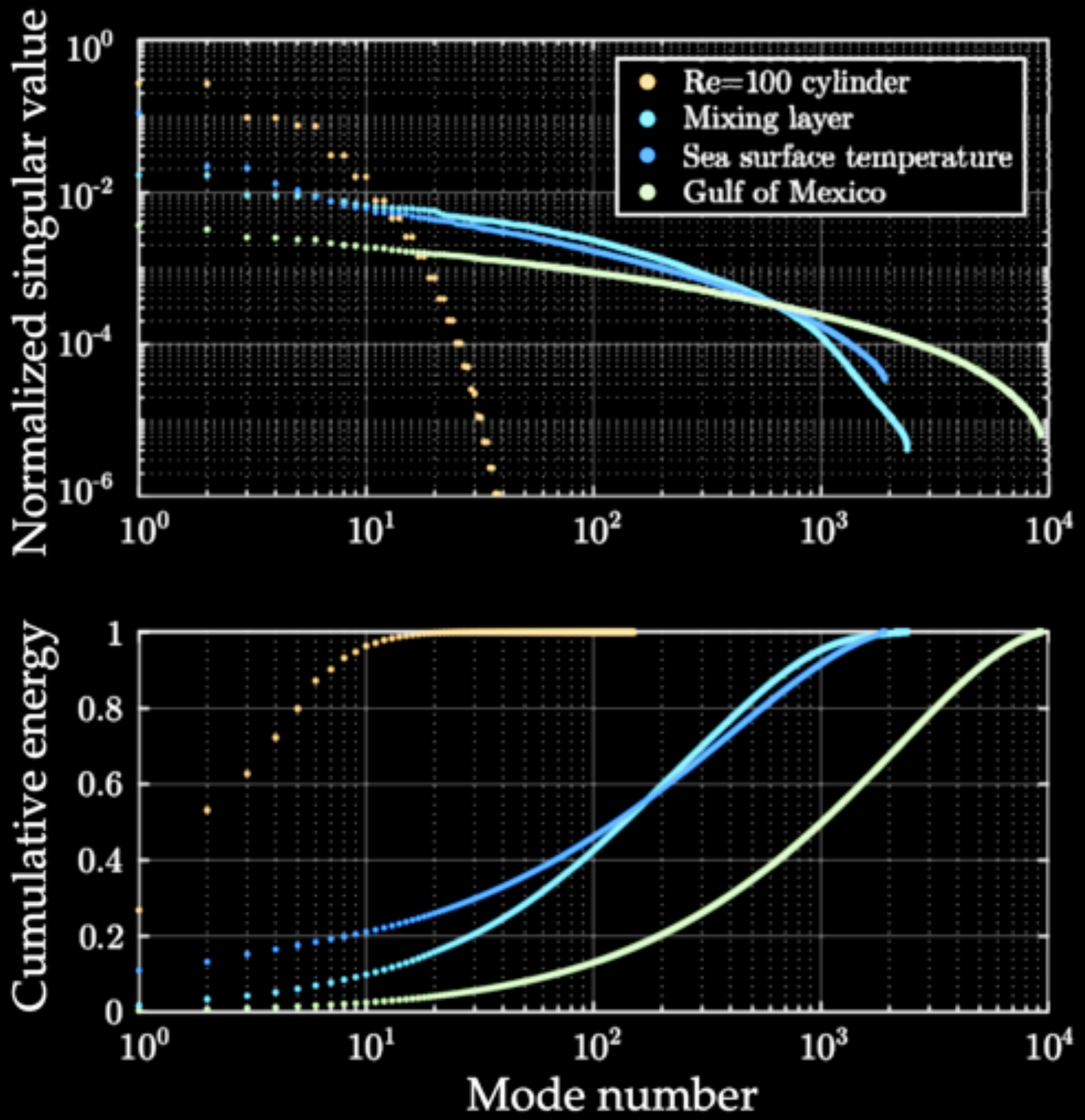






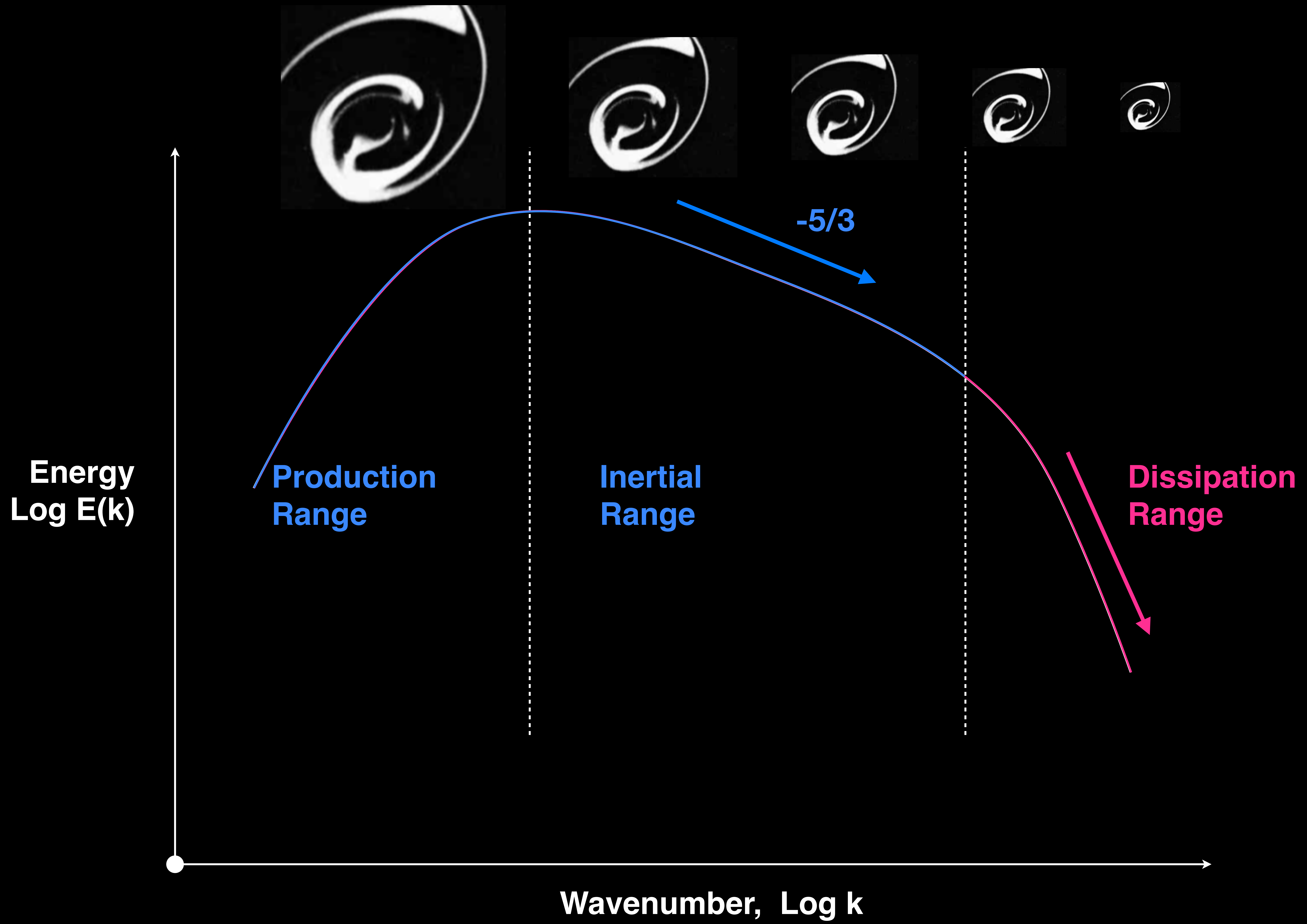
Callaham, Maeda, SLB, *to appear PRF* 2019
[arXiv:1810.06723]

Statistical Stationarity

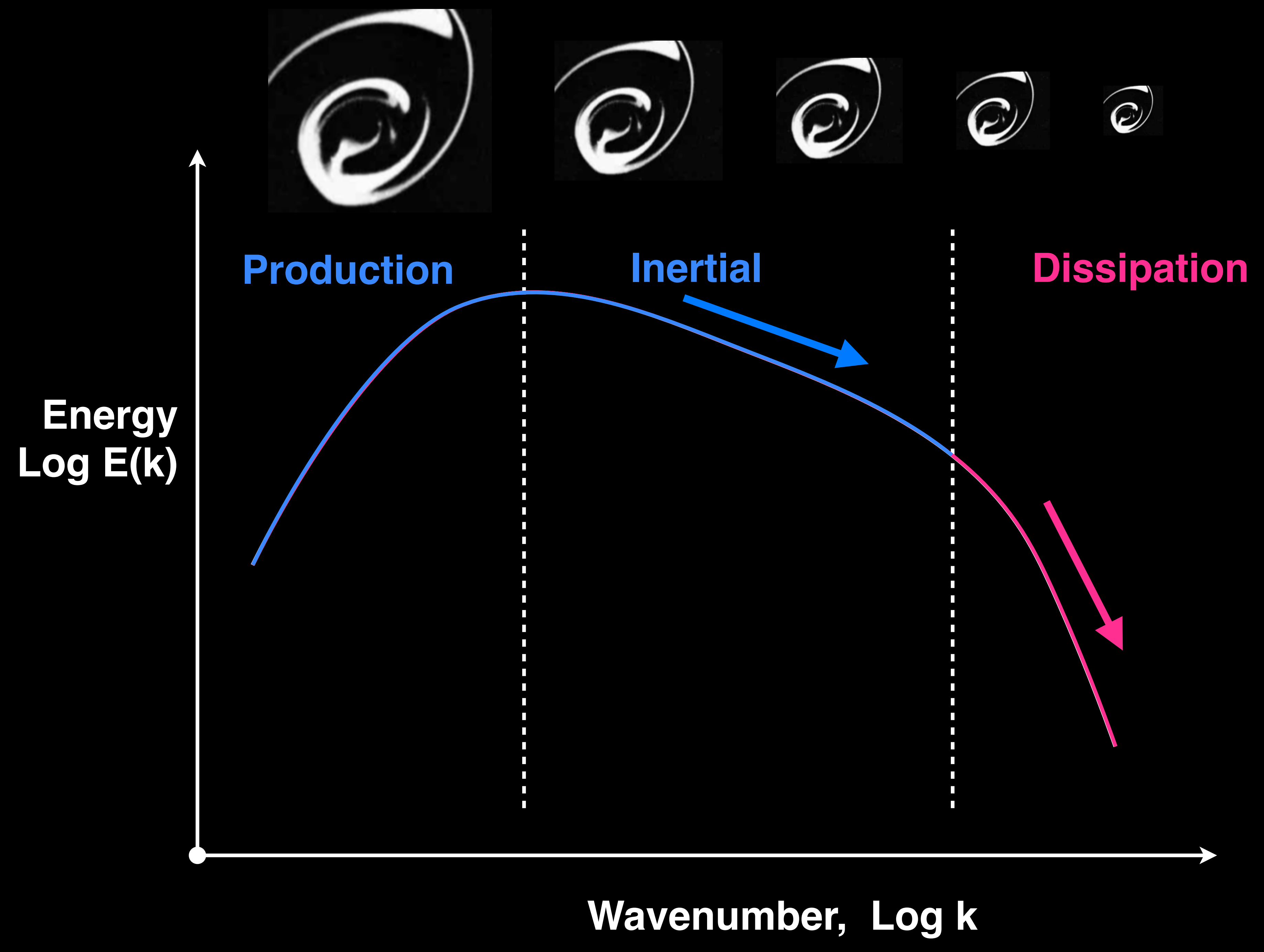


Callaham, Maeda, SLB, *to appear PRF* 2019
[arXiv:1810.06723]

Kolmogorov Energy Cascade



Kolmogorov Energy Cascade

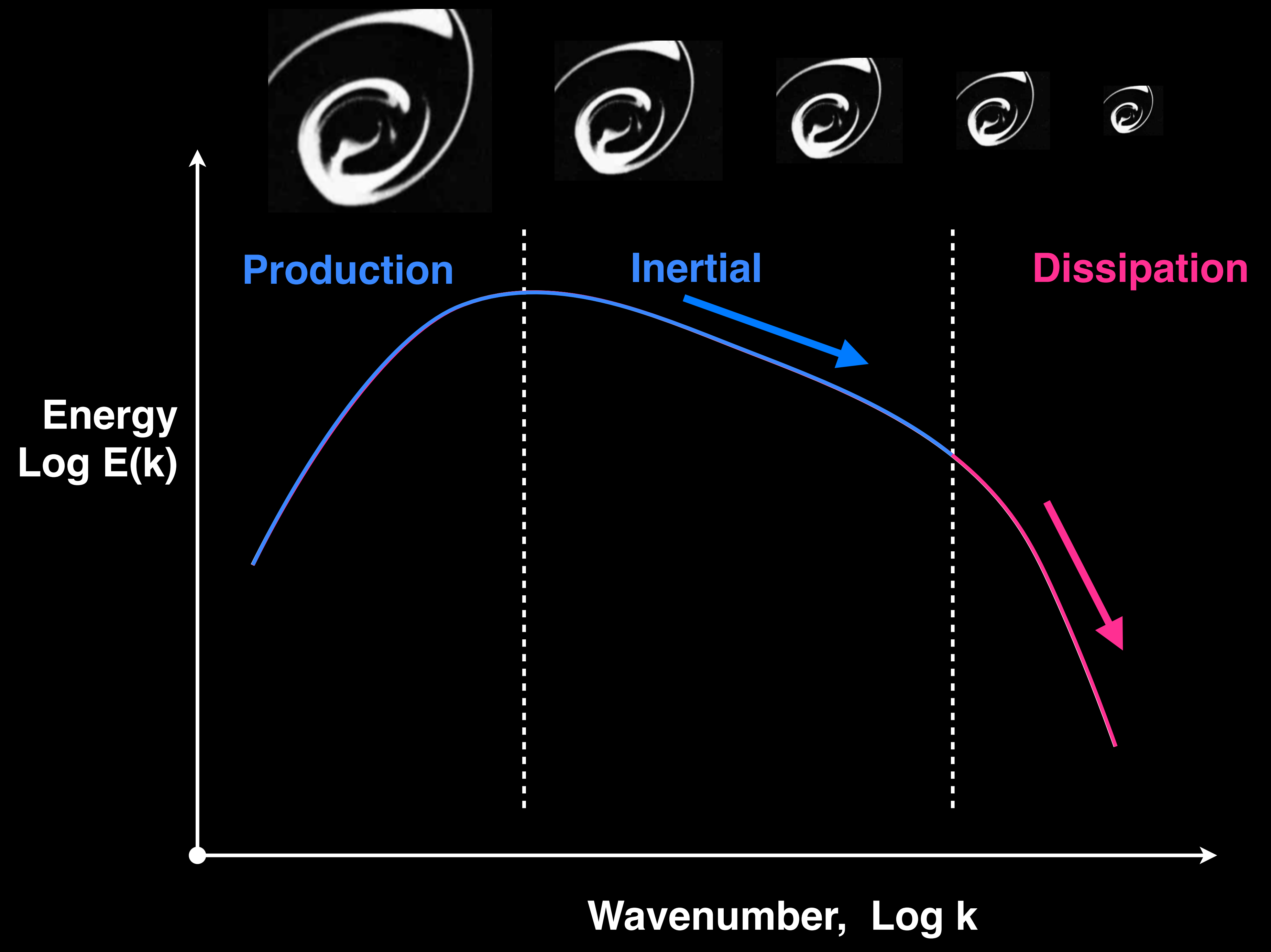


$$\dot{x}_1 = f_1(x_1, x_2, x_3, x_4, \cdots)$$
$$\dot{x}_2 = f_2(x_1, x_2, x_3, x_4, \cdots)$$
$$\dot{x}_3 = f_3(x_1, x_2, x_3, x_4, \cdots)$$
$$\dot{x}_4 = f_4(x_1, x_2, x_3, x_4, \cdots)$$
$$\vdots$$

Can’t resolve all scales…

… don’t want to!

Kolmogorov Energy Cascade



$$\dot{\mathbf{x}}_L = f_L(\mathbf{x}_L, \mathbf{x}_H)$$

$$\dot{\mathbf{x}}_H = f_H(\mathbf{x}_L, \mathbf{x}_H)$$

Approximate effect of **fast/small scales** on **large scales**

$$\mathbf{x}_H = g(\mathbf{x}_L)$$

$$\dot{\mathbf{x}}_L = f_L(\mathbf{x}_L, g(\mathbf{x}_L))$$

Closure Model

RANS - Reynolds Averaged Navier Stokes

Ling & Templeton 2015,
Parish & Duraisamy 2016,
Ling, Kurzawski, Templeton 2016,
Xiao, Wu, Wang, Sun, Roy 2016,
Singh, Medida, Duraisamy, 2017,
Wang, Wu, Xiao, 2017

LES - Large Eddy Simulation

Maulik, San, Rasheed, Vedula 2019

Turbulence Modeling in the Age of Data

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[2]Department of Mechanical Engineering, Stanford University, Stanford, CA 94305; jops@stanford.edu
[3]Kevin T. Crofton Department of Aerospace and Ocean Engineering, Virginia Tech, Blacksburg, VA 24060; hengxiao@vt.edu
[†] Contributed equally. Author list is alphabetical.

Xxxx. Xxx. Xxx. Xxx. YYYY. AA:1–22

https://doi.org/10.1146/((please add article doi))

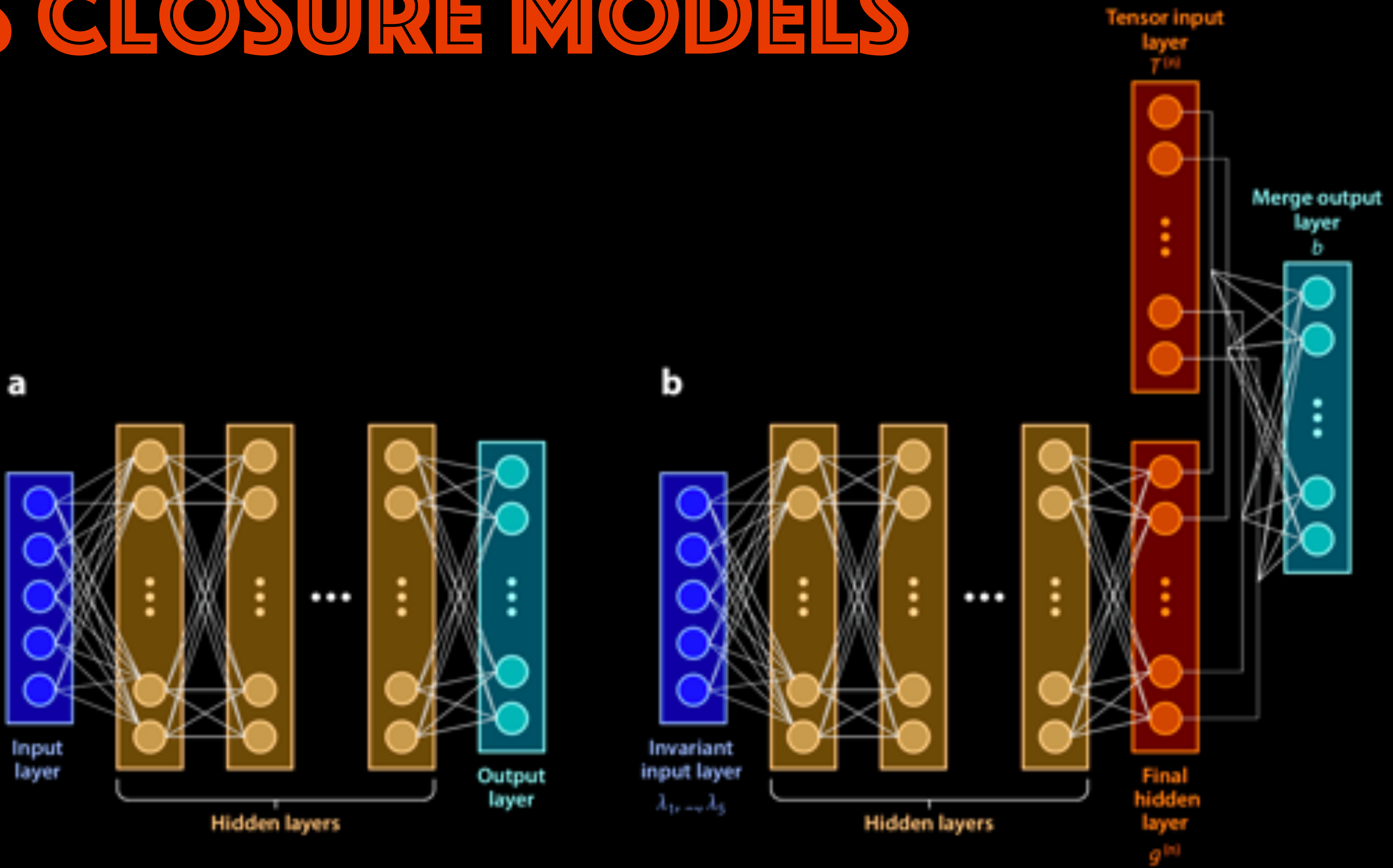
Keywords

turbulence modeling, statistical inference, machine learning, data-driven modeling, uncertainty quantification

Abstract

Data from experiments and direct simulations of turbulence have historically been used to *calibrate* simple engineering models such as those based on the Reynolds-averaged Navier–Stokes (RANS) equations. In the past few years, with the availability of large and diverse datasets, researchers have begun to explore methods to *systematically inform* turbulence models with data, with the goal of quantifying and reducing model uncertainties. This review surveys recent developments in bounding uncertainties in RANS models via physical constraints, in adopting statistical inference to characterize model coefficients and estimate discrepancy, and in using machine learning to improve turbulence models. Key principles, achievements and challenges are discussed. A central perspective advocated in this review is that by exploiting foundational knowledge in turbulence modeling and physical constraints, data-driven approaches can yield useful predictive models.

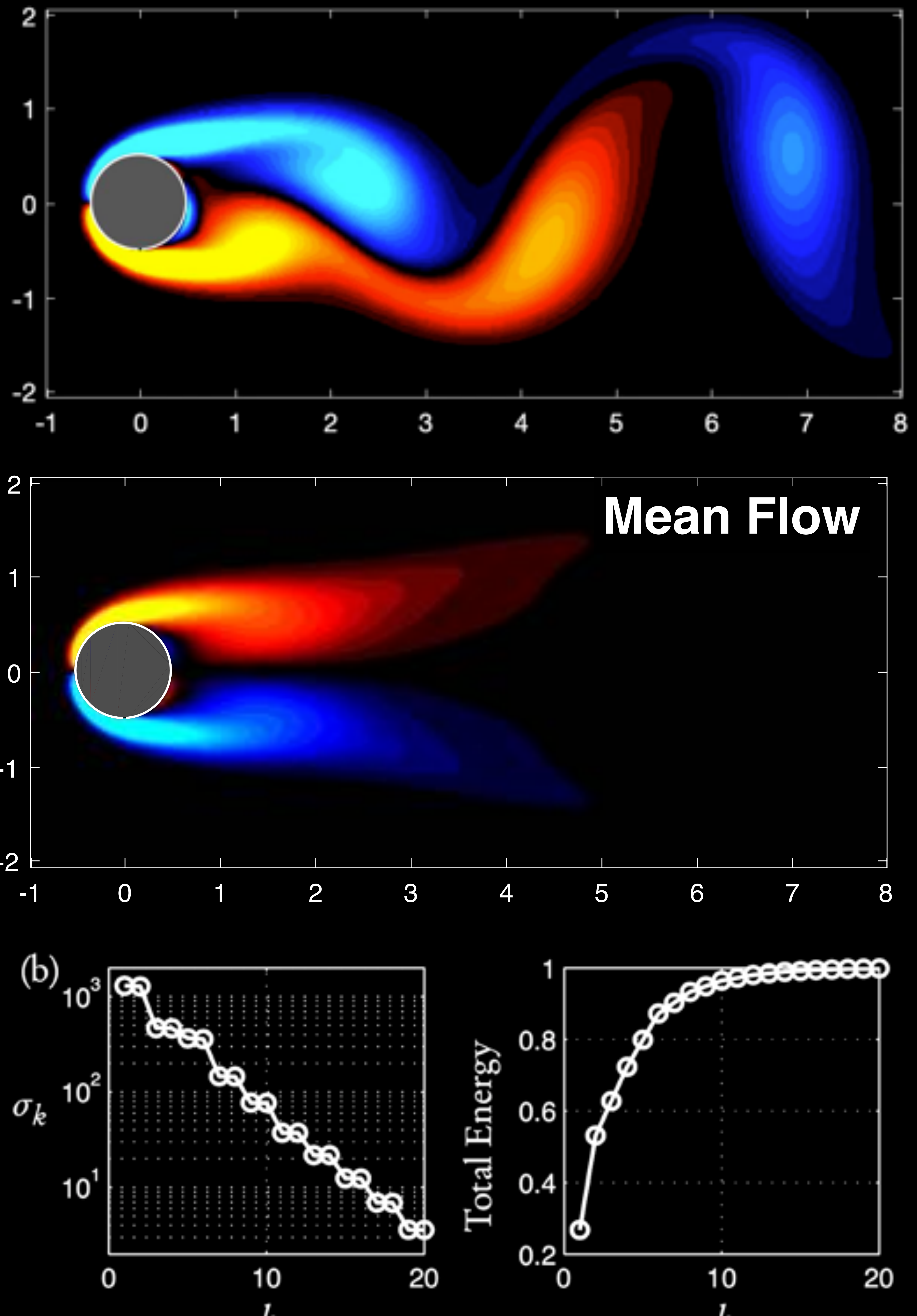
RANS CLOSURE MODELS

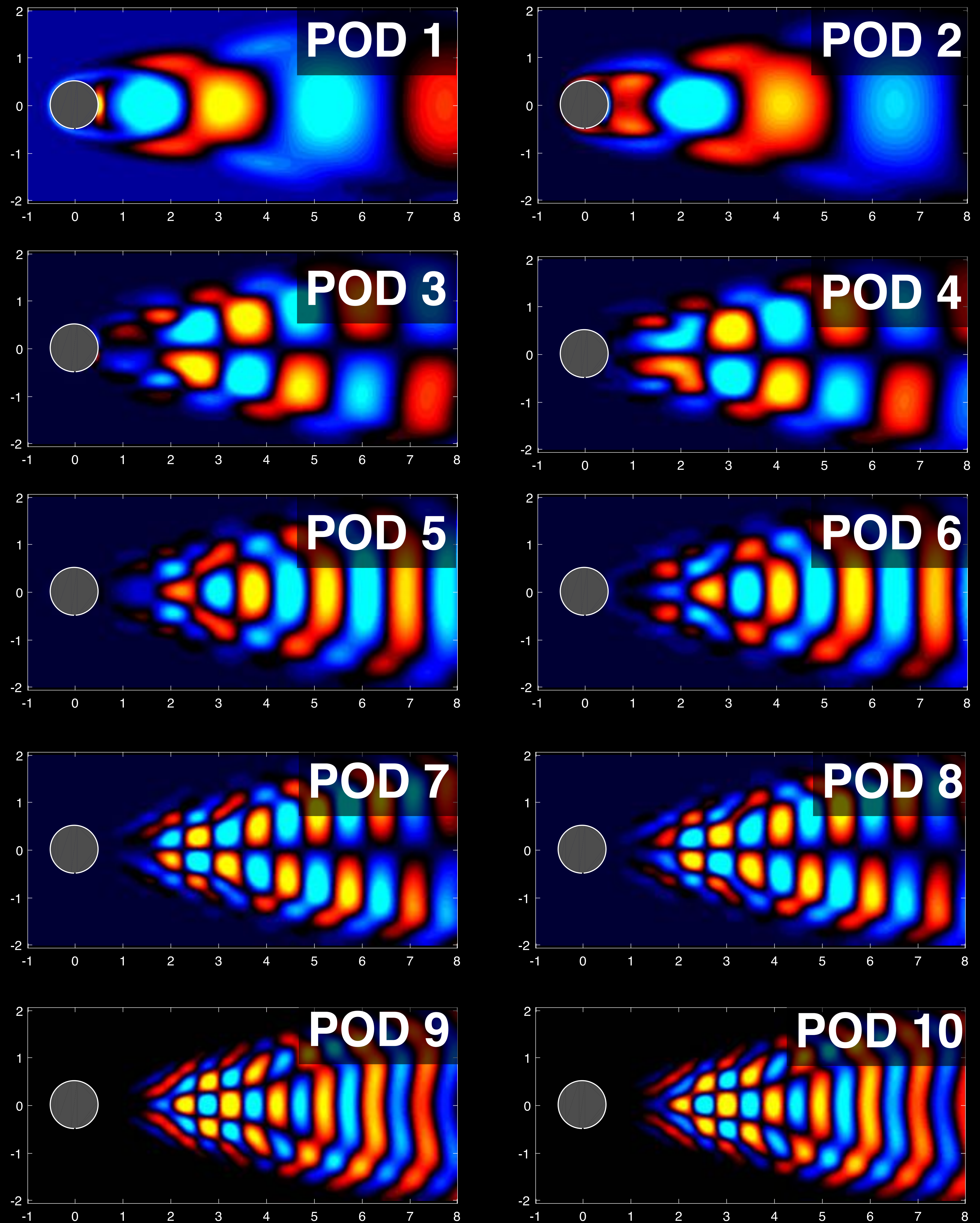


Ling, Kurzawski, Templeton, *JFM*, 807, 2016

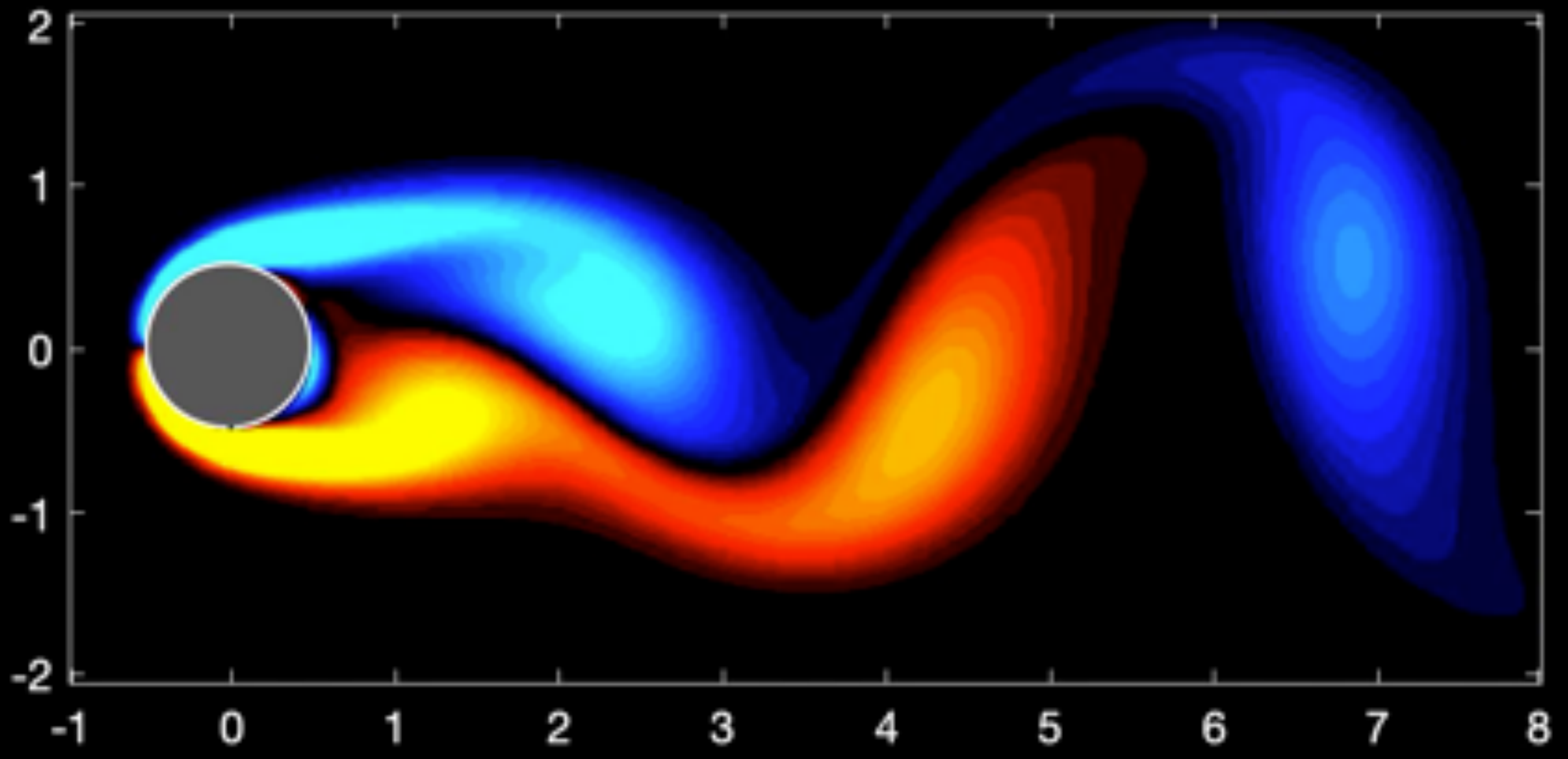
POD/PCA

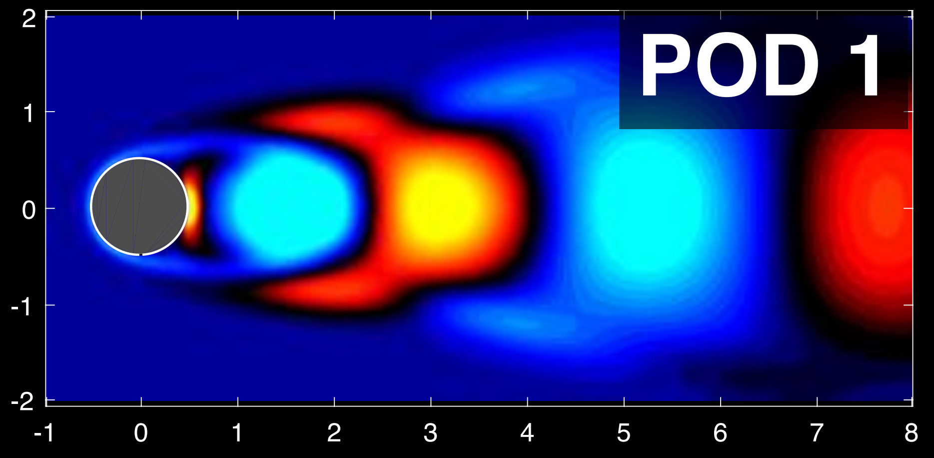
$$\mathbf{u}(\mathbf{x},t) \approx \bar{\mathbf{u}} + \sum_{k=1}^{r} \boldsymbol{\varphi}_k(\mathbf{x})\mathbf{a}_k(t)$$

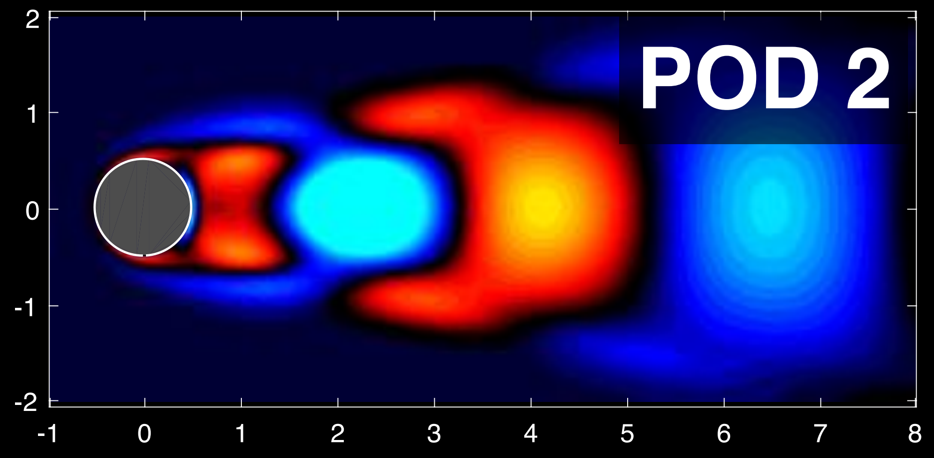


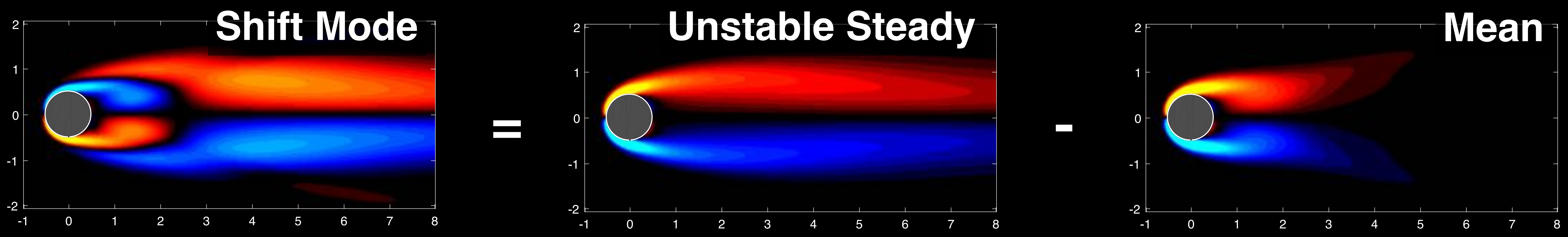


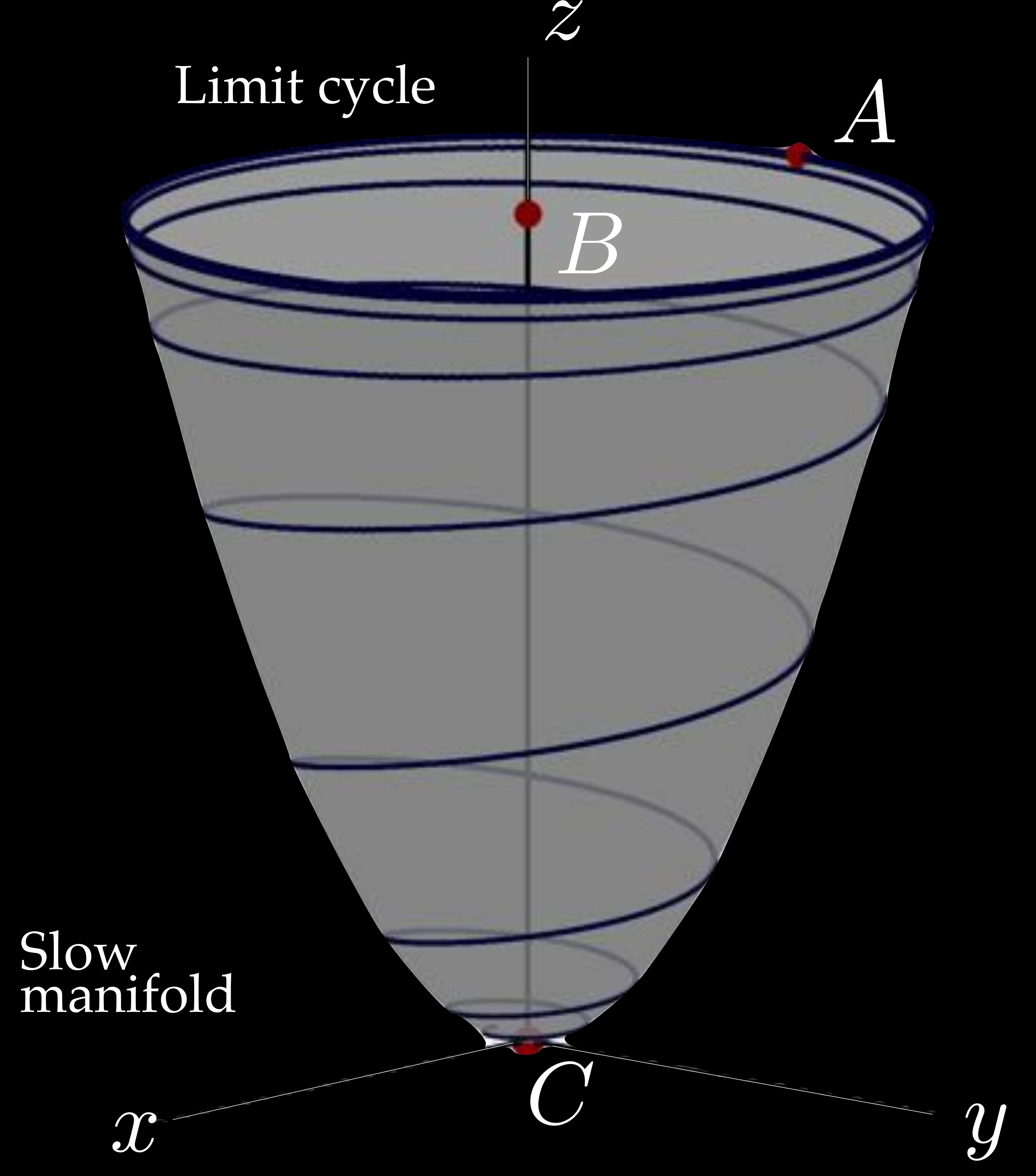
REDUCED ORDER MODELS







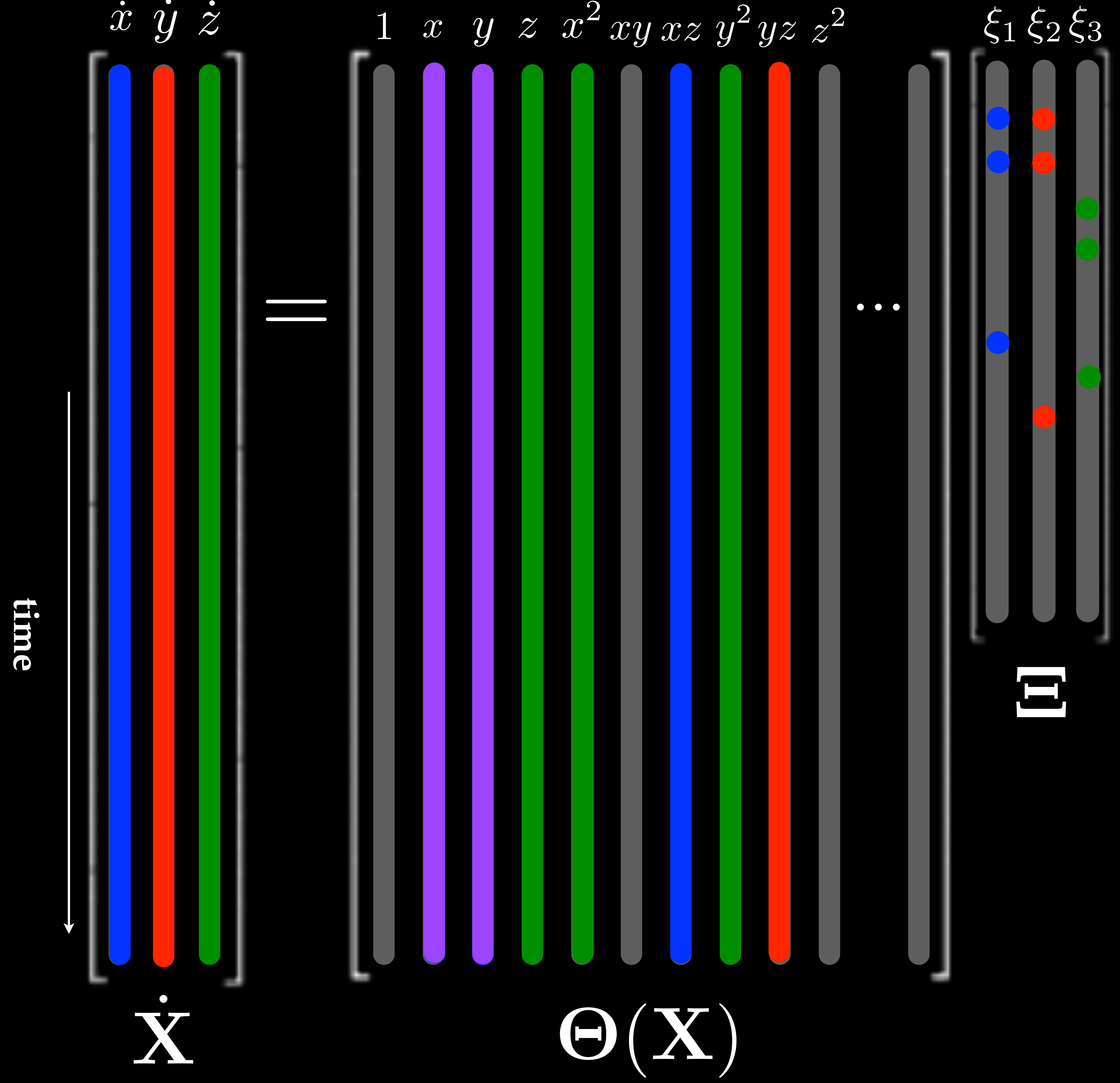


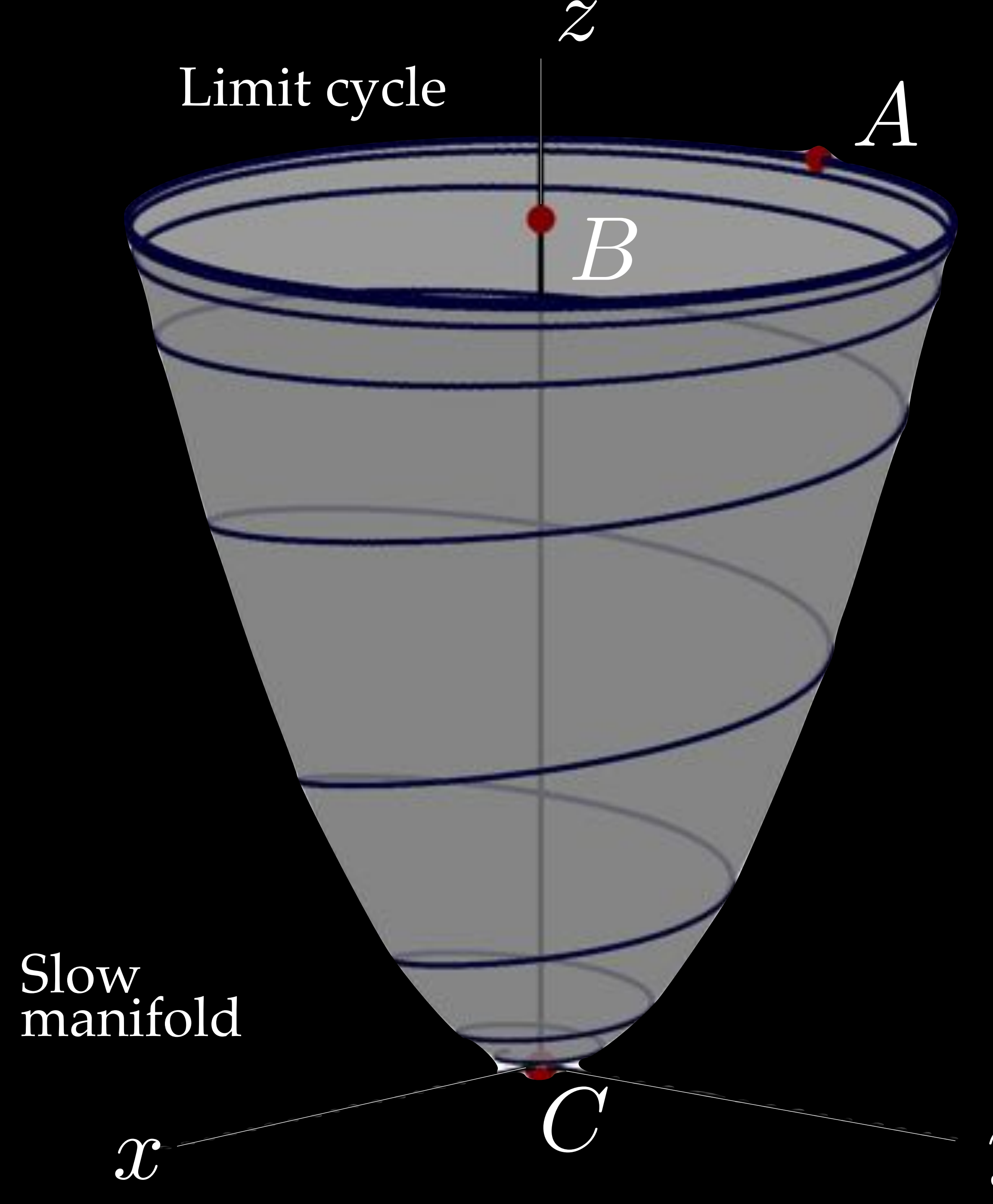


$$
\begin{aligned}
\dot{x} &= \mu x - \omega y + Axz \\
\dot{y} &= \omega x + \mu y + Ayz \\
\dot{z} &= -\lambda(z - x^2 - y^2).
\end{aligned}
$$

Ruelle and Takens, 1971
Noack *et al.*, JFM 2003.

Sparse Identification of Nonlinear Dynamics (SINDy)





$$
\begin{aligned}
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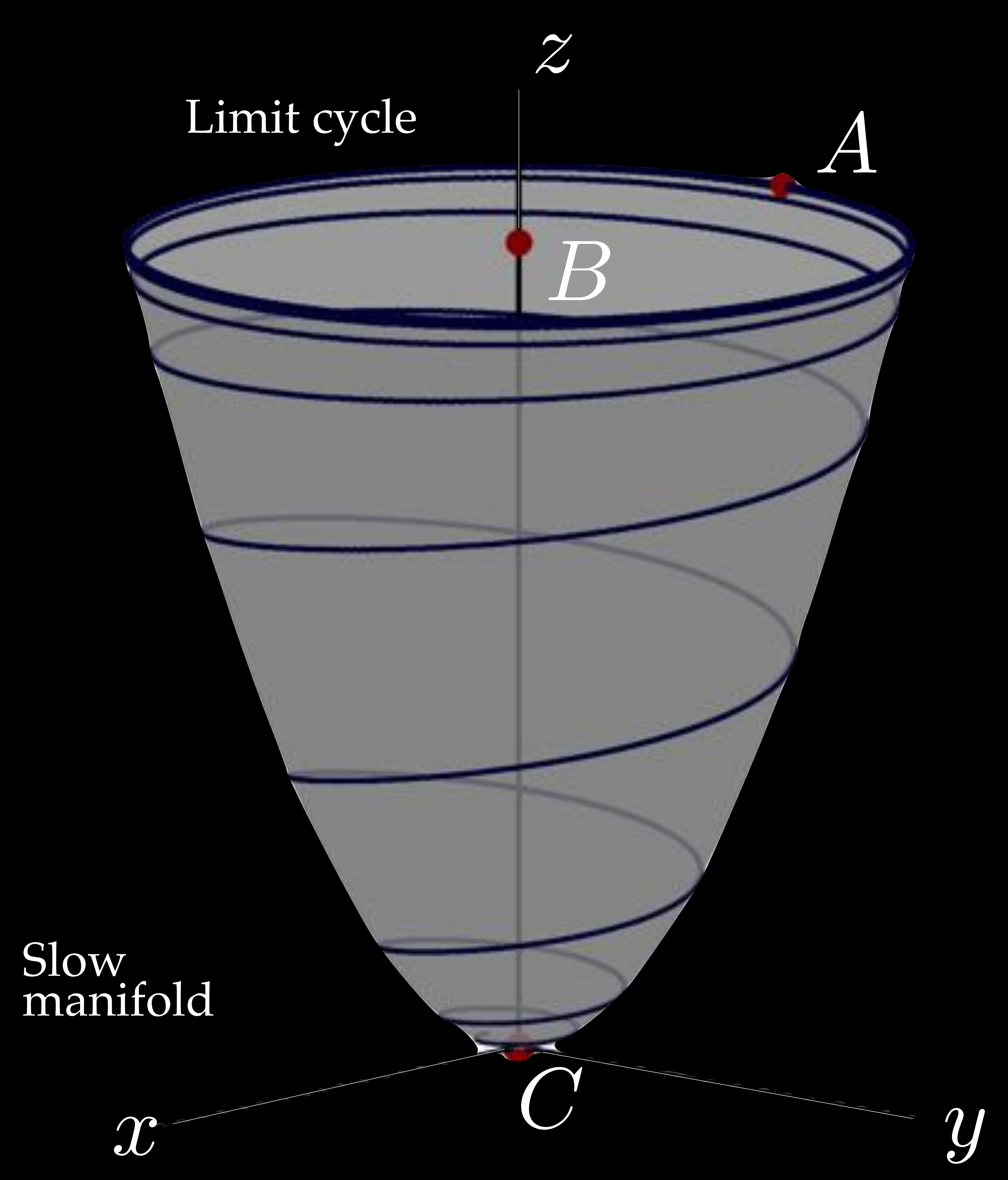
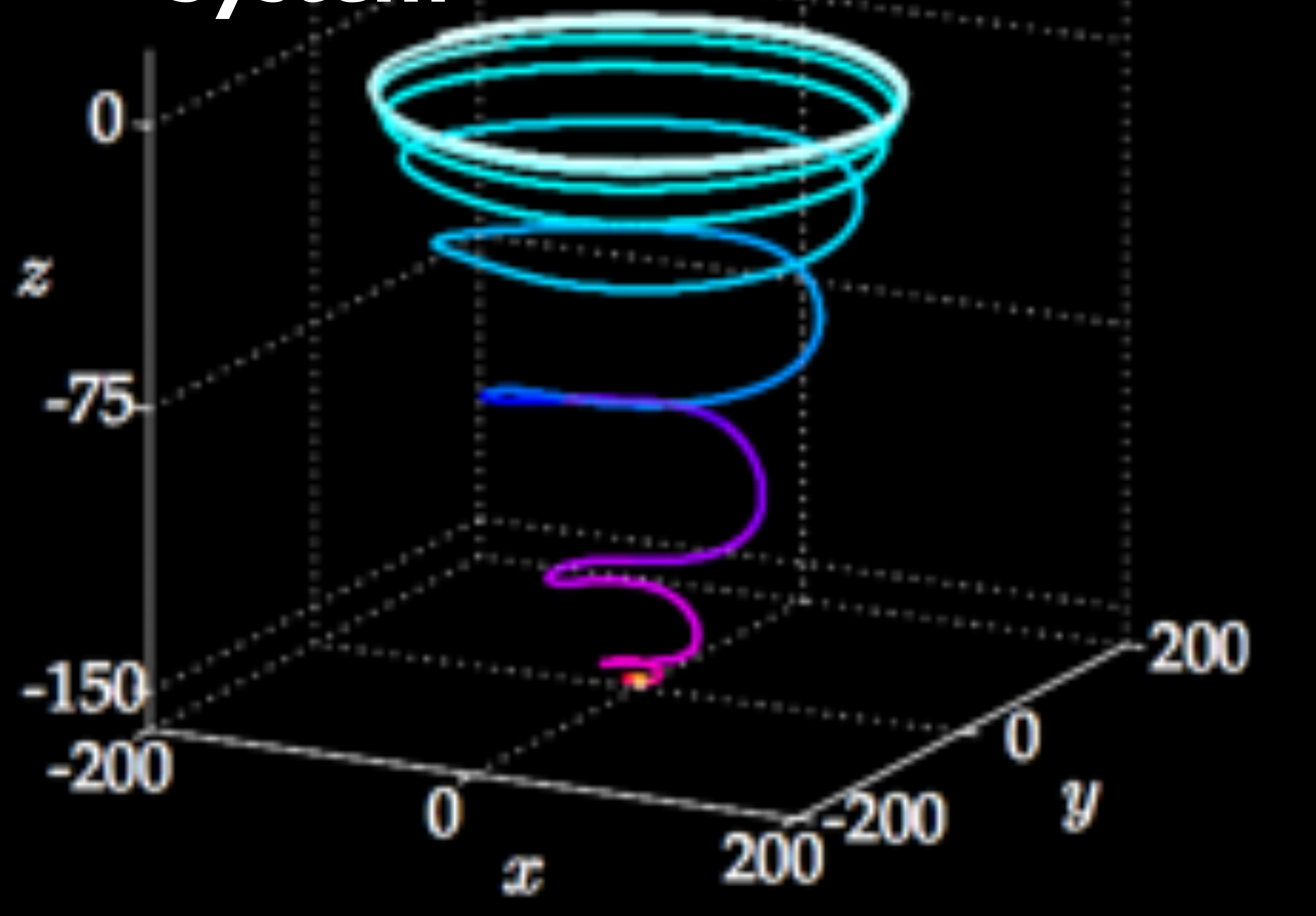
\dot{y} &= \omega x + \mu y + Ayz \\
\dot{z} &= -\lambda(z - x^2 - y^2).
\end{aligned}
$$

SLB, Proctor, Kutz, *PNAS* 2016.

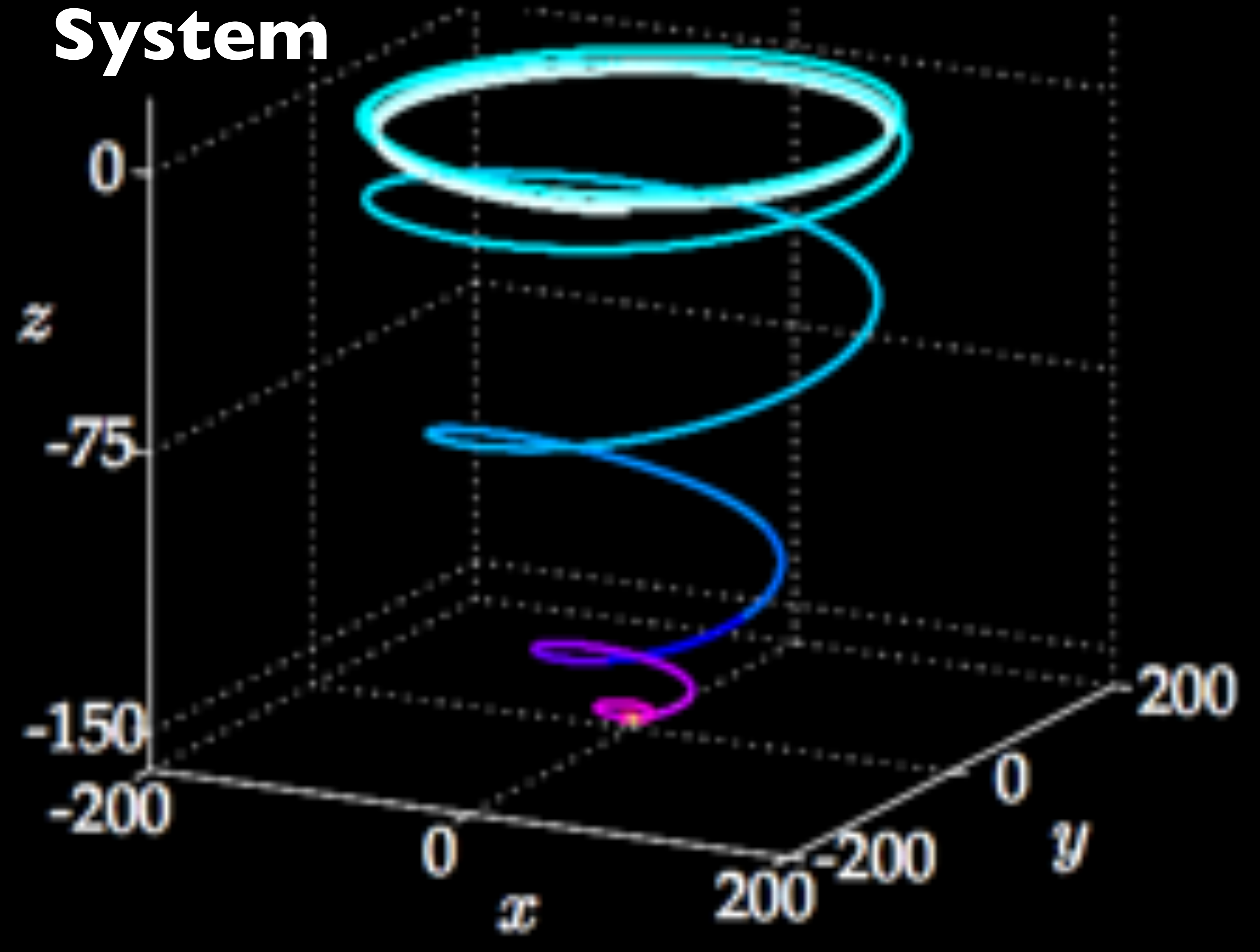
Constrained Sparse Galerkin Regression

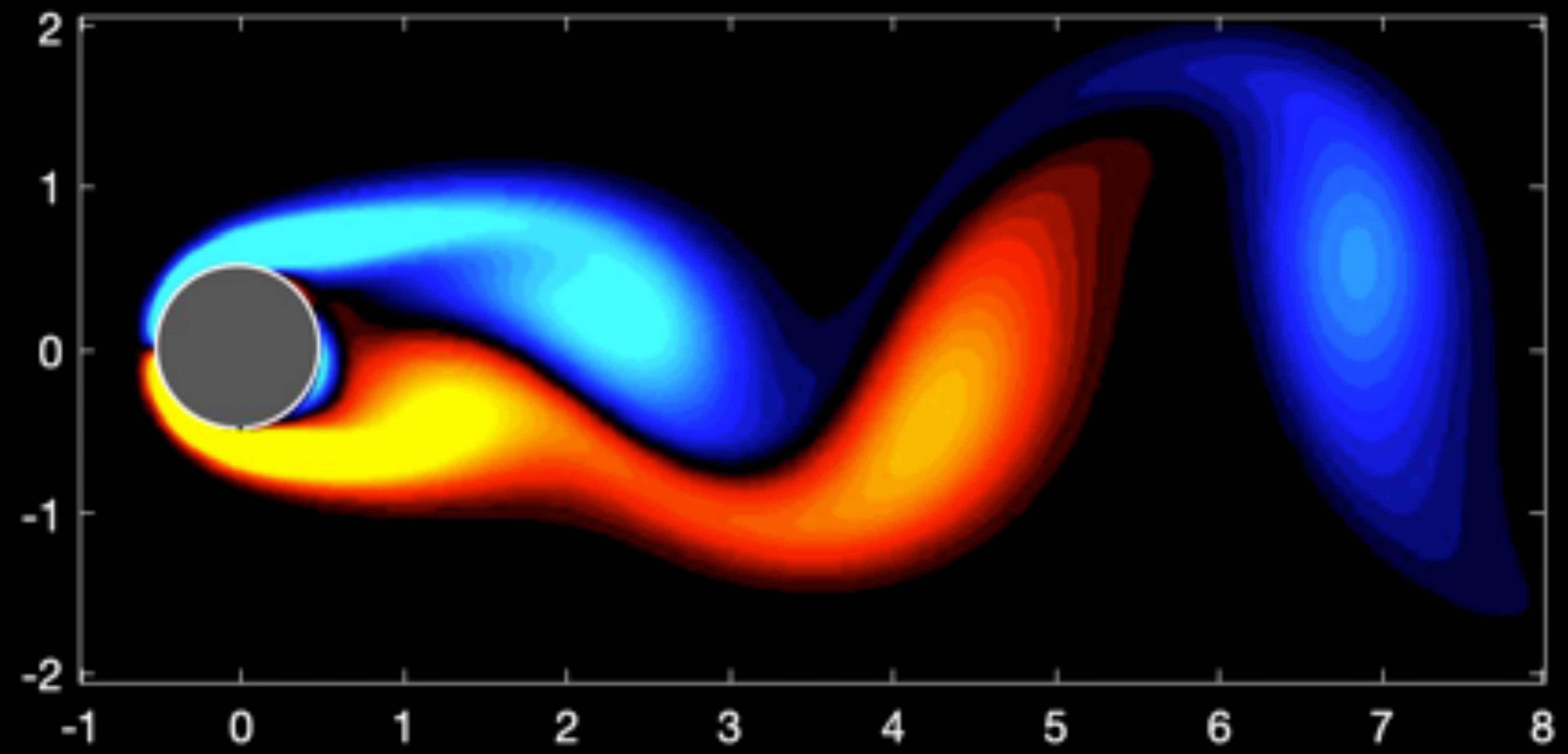


Full System



Identified System





$$
\begin{aligned}
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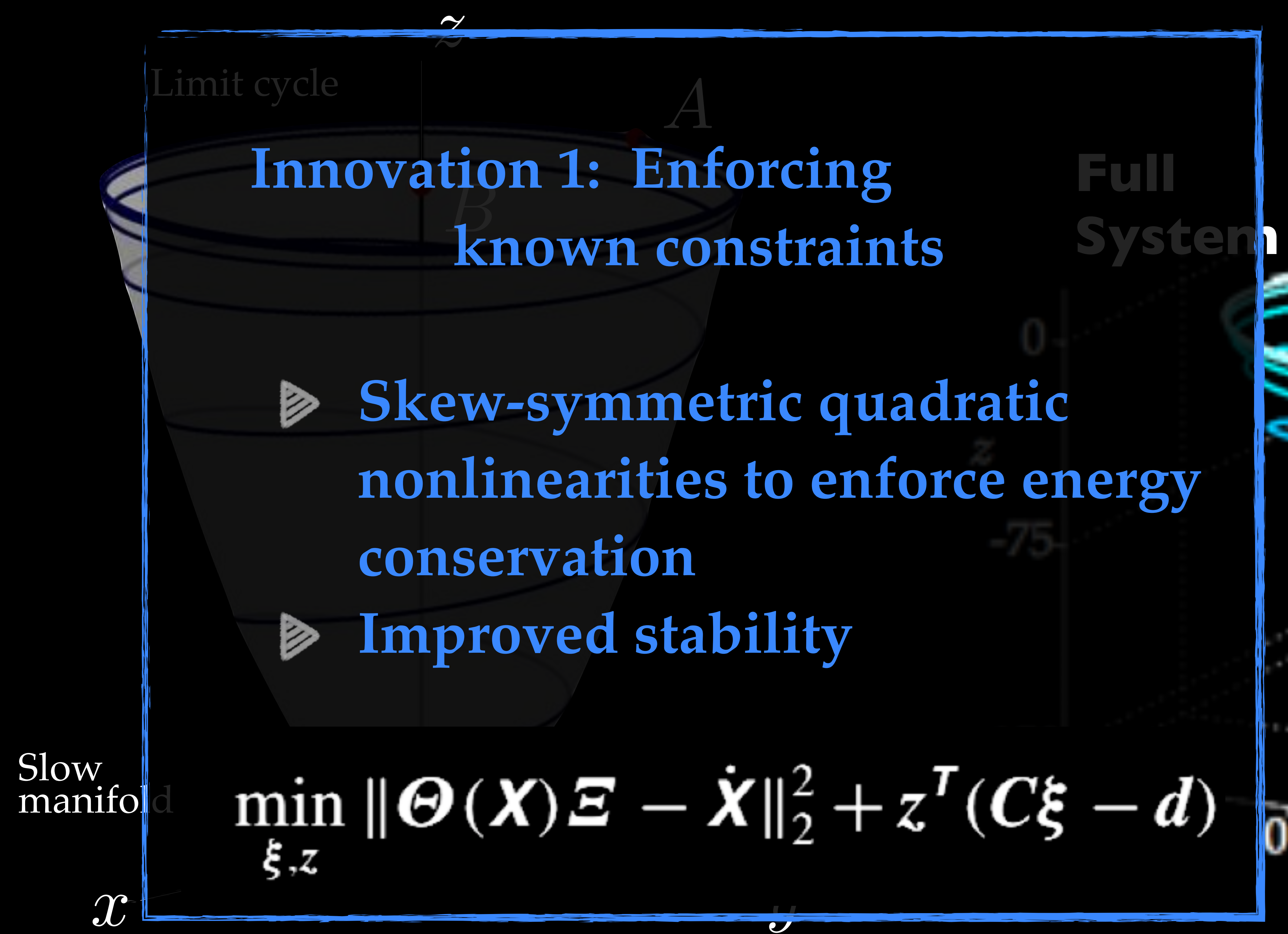
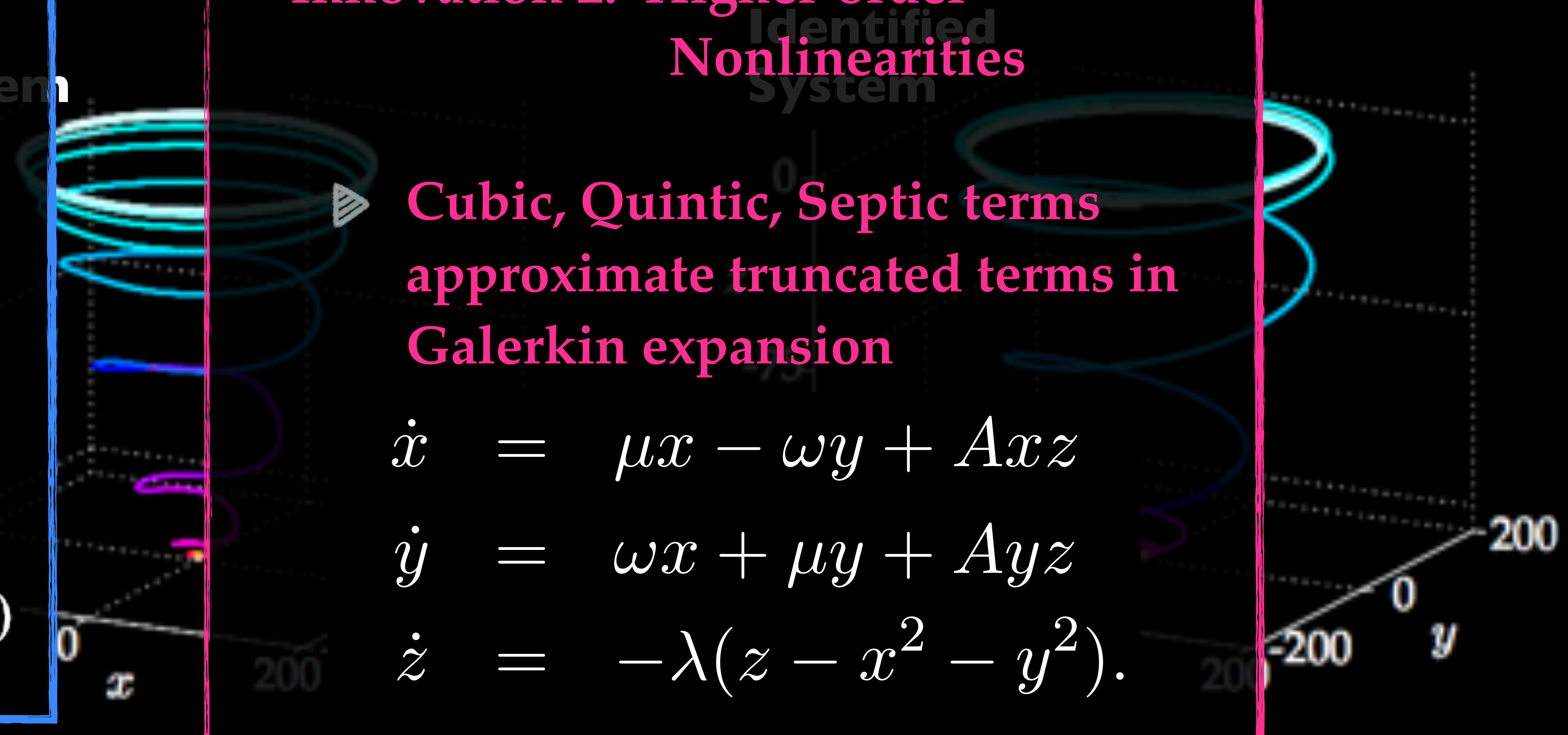
\dot{y} &= \omega x + \mu y + Ayz \\
\dot{z} &= -\lambda(z - x^2 - y^2).
\end{aligned}
$$

Loiseau & SLB, *JFM* 838, 2018

Constrained Sparse Galerkin Regression





Innovation 1: Enforcing known constraints

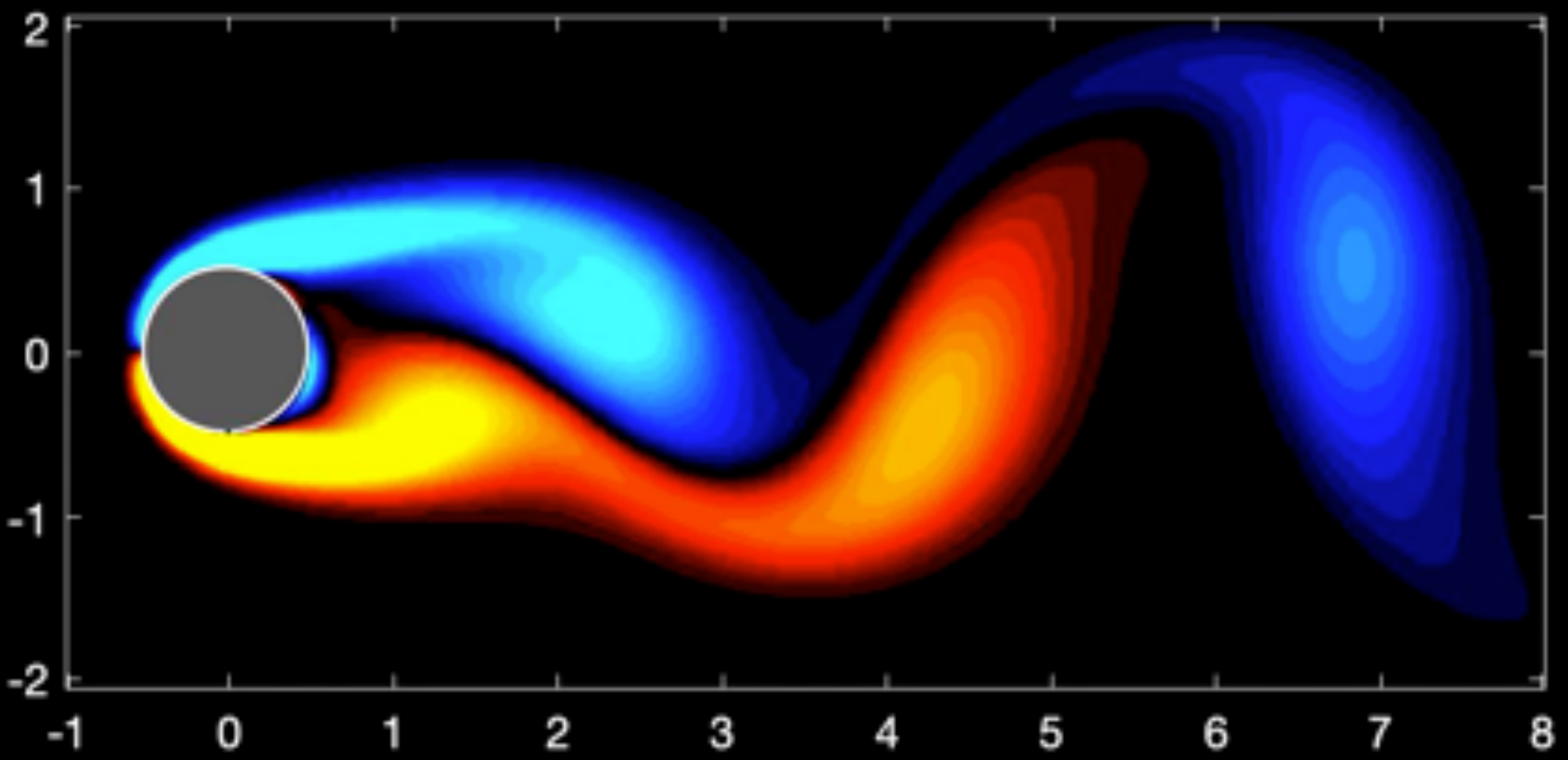
- Skew-symmetric quadratic nonlinearities to enforce energy conservation
- Improved stability

$$\min_{\xi, z} \|\Theta(X)\Xi - \dot{X}\|_2^2 + z^T(C\xi - d)$$

Innovation 2: Higher-order Nonlinearities

- Cubic, Quintic, Septic terms approximate truncated terms in Galerkin expansion

$$\begin{aligned} \dot{x} &= \mu x - \omega y + Axz \\ \dot{y} &= \omega x + \mu y + Ayz \\ \dot{z} &= -\lambda(z - x^2 - y^2). \end{aligned}$$



$$\begin{aligned} \dot{x} &= \mu x - \omega y + Axz \\ \dot{y} &= \omega x + \mu y + Ayz \\ \dot{z} &= -\lambda(z - x^2 - y^2). \end{aligned}$$

Loiseau & SLB, *JFM* 838, 2018

Constrained Sparse Galerkin Regression

Innovation 1: Enforcing known constraints

$$\int_\Omega \boldsymbol{u} \cdot (\boldsymbol{u} \cdot \nabla)\boldsymbol{u} \, \mathrm{d}\Omega = 0 \;\Rightarrow\; \boldsymbol{a} \cdot \mathcal{N}(\boldsymbol{a}) = 0$$

- Skew-symmetric quadratic nonlinearities to enforce energy conservation
- Improved stability

$$0 = \begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} \begin{bmatrix} \xi_4^{(a_1)} a_1 & \xi_5^{(a_1)} a_1 + \xi_7^{(a_1)} a_2 & \xi_6^{(a_1)} a_1 + \xi_9^{(a_1)} a_3 \\ \xi_4^{(a_2)} a_1 + \xi_5^{(a_2)} a_2 & \xi_7^{(a_2)} a_2 & \xi_8^{(a_2)} a_2 + \xi_9^{(a_2)} a_3 \\ \xi_4^{(a_3)} a_1 + \xi_6^{(a_3)} a_3 & \xi_7^{(a_3)} a_2 + \xi_8^{(a_3)} a_3 & \xi_9^{(a_3)} a_3 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} \begin{bmatrix} \xi_8^{(a_1)} a_2 a_3 \\ \xi_6^{(a_2)} a_1 a_3 \\ \xi_5^{(a_3)} a_1 a_2 \end{bmatrix}.$$

Loiseau & SLB, *JFM* 838, 2018

Constrained Sparse Galerkin Regression

Innovation 1: Enforcing known constraints

$$\int_{\Omega} \boldsymbol{u} \cdot (\boldsymbol{u} \cdot \nabla)\boldsymbol{u} \, \mathrm{d}\Omega = 0 \quad \Rightarrow \quad \boldsymbol{a} \cdot \mathcal{N}(\boldsymbol{a}) = 0$$

- Skew-symmetric quadratic nonlinearities to enforce energy conservation
- Improved stability

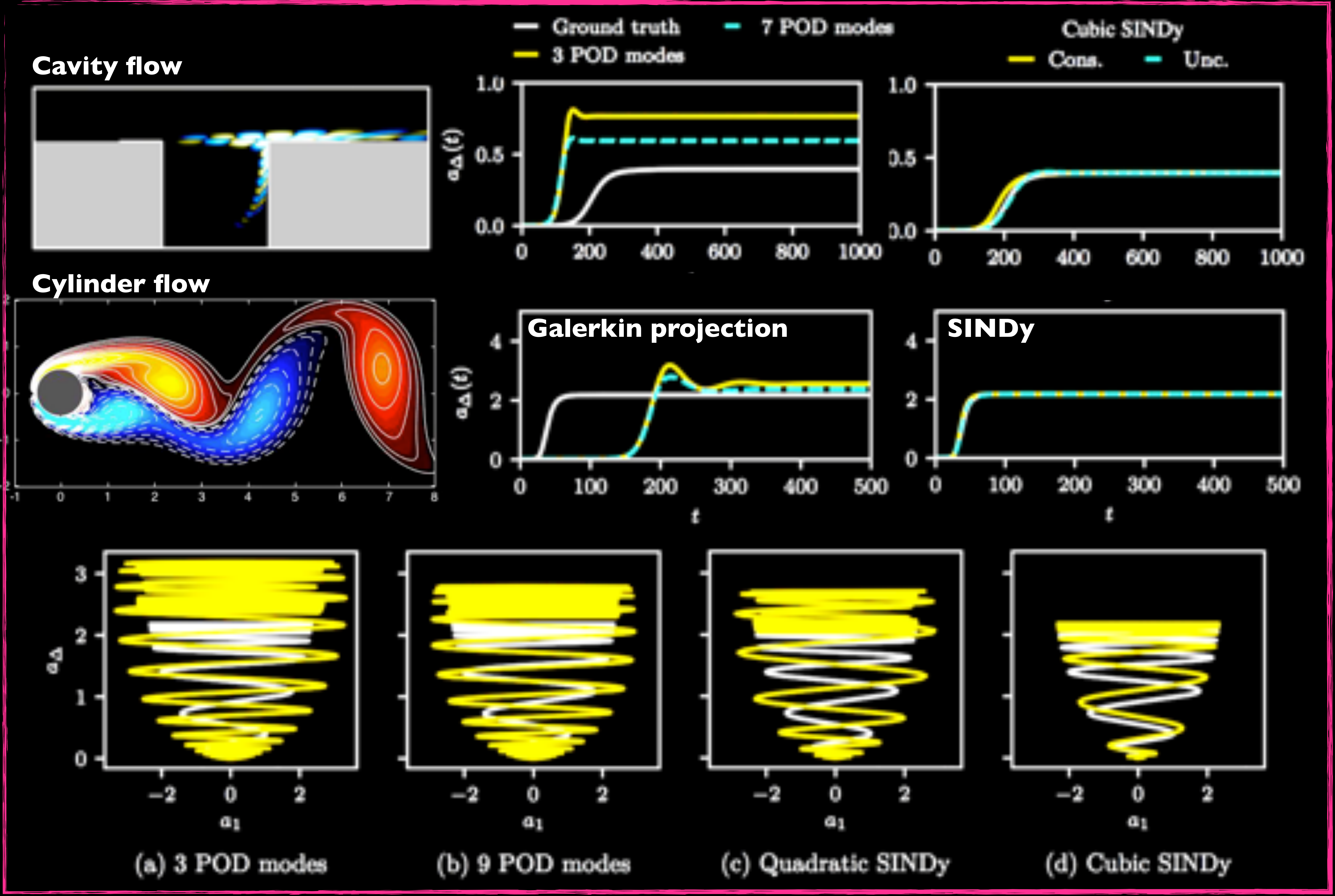
$$\left.\begin{aligned}
\xi_8^{(a_1)} + \xi_6^{(a_2)} + \xi_5^{(a_3)} &= 0, \\
\xi_4^{(a_1)} = \xi_7^{(a_2)} = \xi_9^{(a_3)} &= 0, \\
\xi_5^{(a_1)} &= -\xi_4^{(a_2)}, \\
\xi_7^{(a_1)} &= -\xi_5^{(a_2)}, \\
\xi_6^{(a_1)} &= -\xi_4^{(a_3)}, \\
\xi_9^{(a_1)} &= -\xi_6^{(a_3)}, \\
\xi_8^{(a_2)} &= -\xi_7^{(a_3)}, \\
\xi_9^{(a_2)} &= -\xi_8^{(a_3)},
\end{aligned}\right\}$$

$$\min_{\xi, z} \|\boldsymbol{\Theta}(\boldsymbol{X})\boldsymbol{\Xi} - \dot{\boldsymbol{X}}\|_2^2 + z^T(C\xi - \boldsymbol{d})$$

$$\begin{bmatrix} 2\hat{\boldsymbol{\Theta}}(\boldsymbol{X})^T\hat{\boldsymbol{\Theta}}(\boldsymbol{X}) & \boldsymbol{C}^T \\ \boldsymbol{C} & 0 \end{bmatrix} \begin{bmatrix} \xi \\ z \end{bmatrix} = \begin{bmatrix} 2\hat{\boldsymbol{\Theta}}(\boldsymbol{X})^T\dot{\boldsymbol{X}}(:) \\ \boldsymbol{d} \end{bmatrix}$$

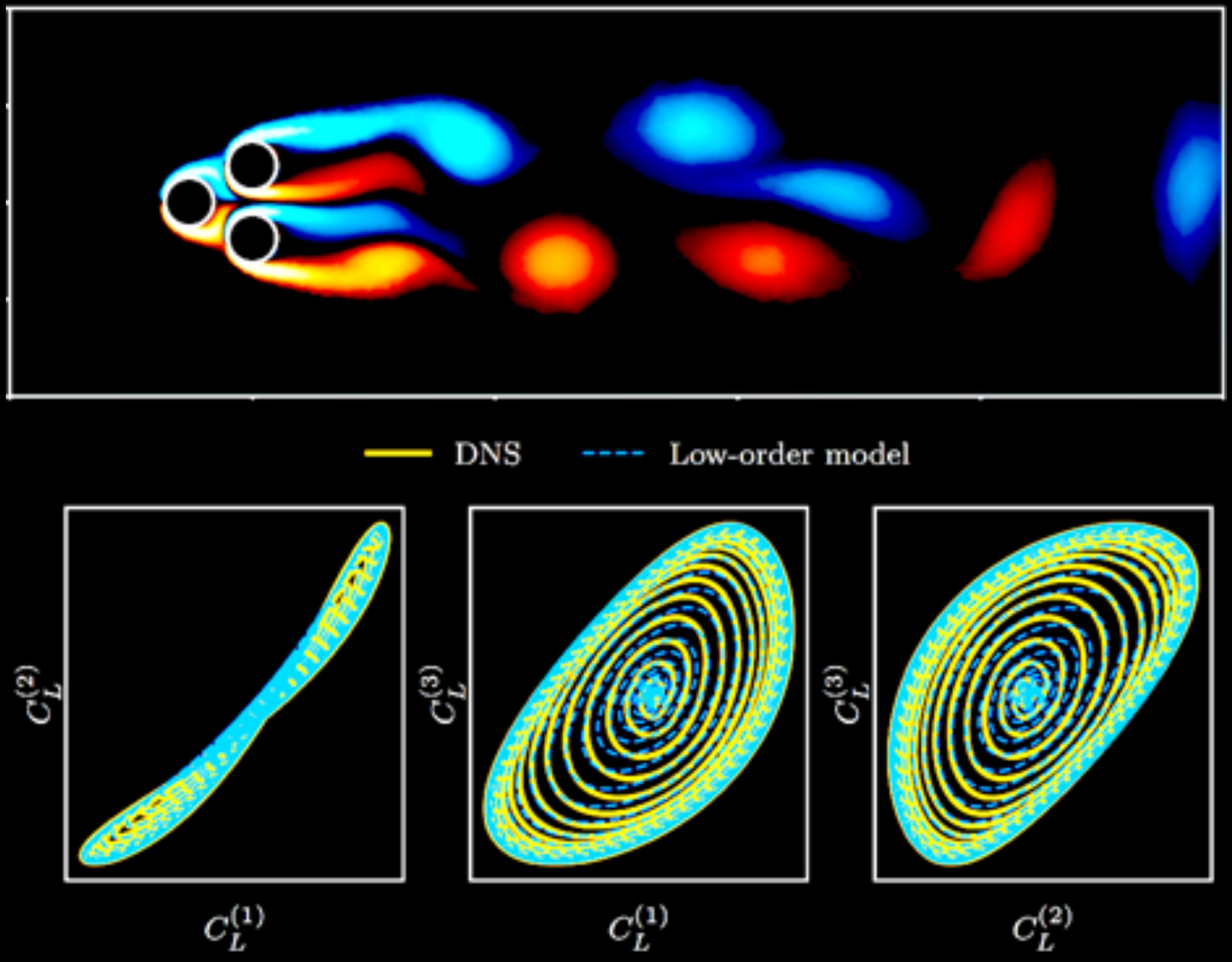
Loiseau & SLB, *JFM* 838, 2018

Constrained Sparse Galerkin Regression



Loiseau & SLB, *JFM* 838, 2018

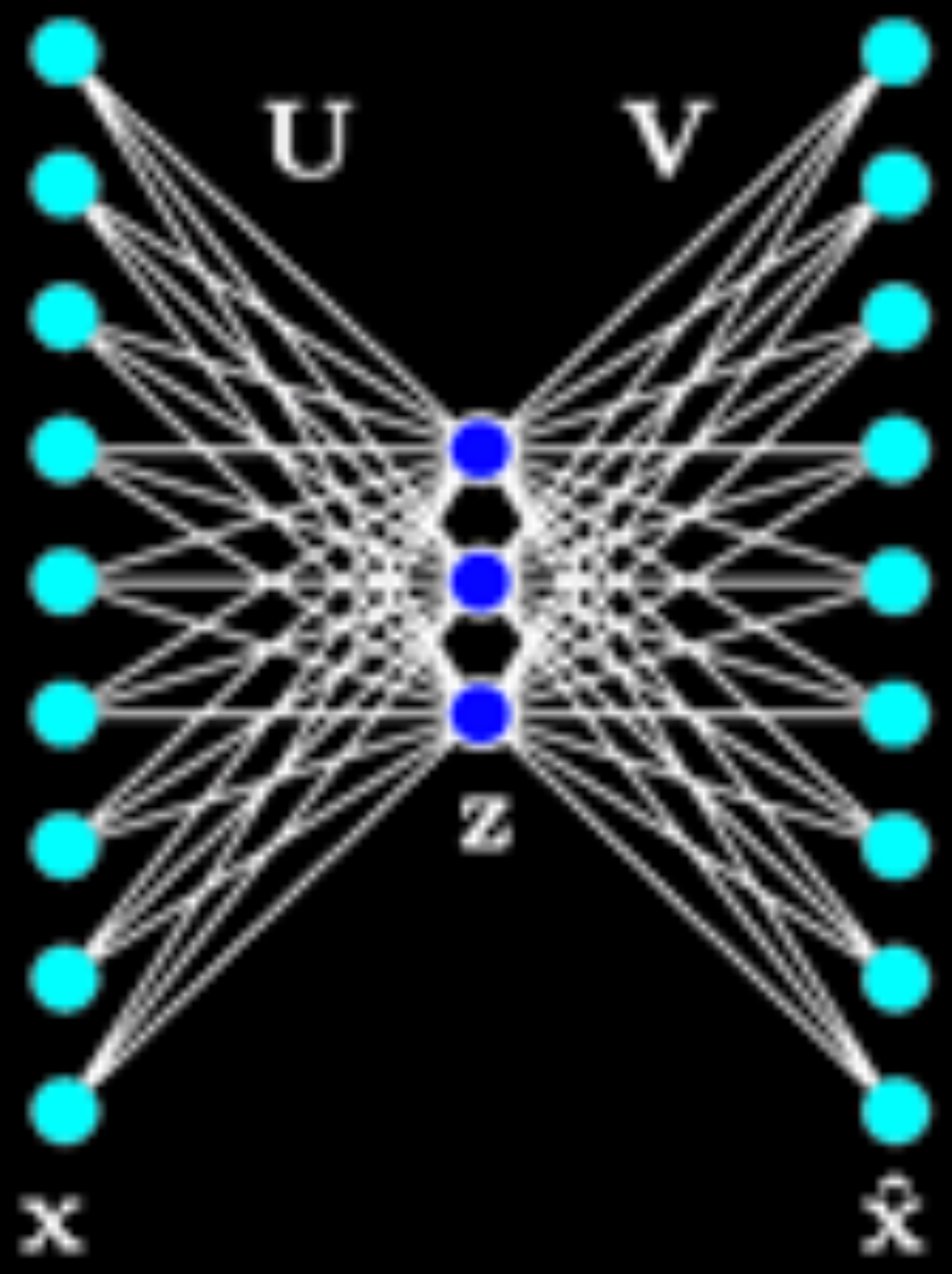
More Complex Flow: Fluidic Pinball



Loiseau, Noack, SLB, *JFM* 844, 2018

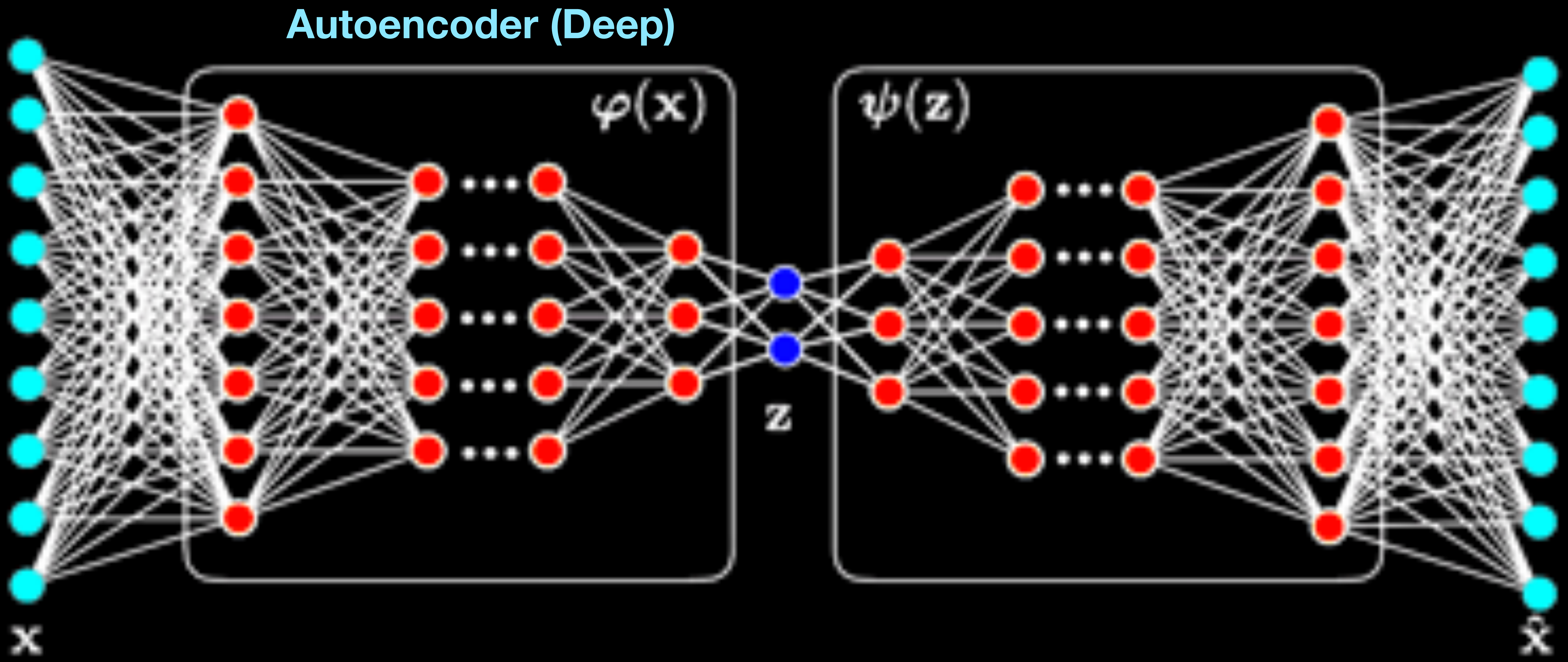
POD/PCA

Autoencoder (Shallow, linear)



Principal
Component
Analysis

BEYOND POD

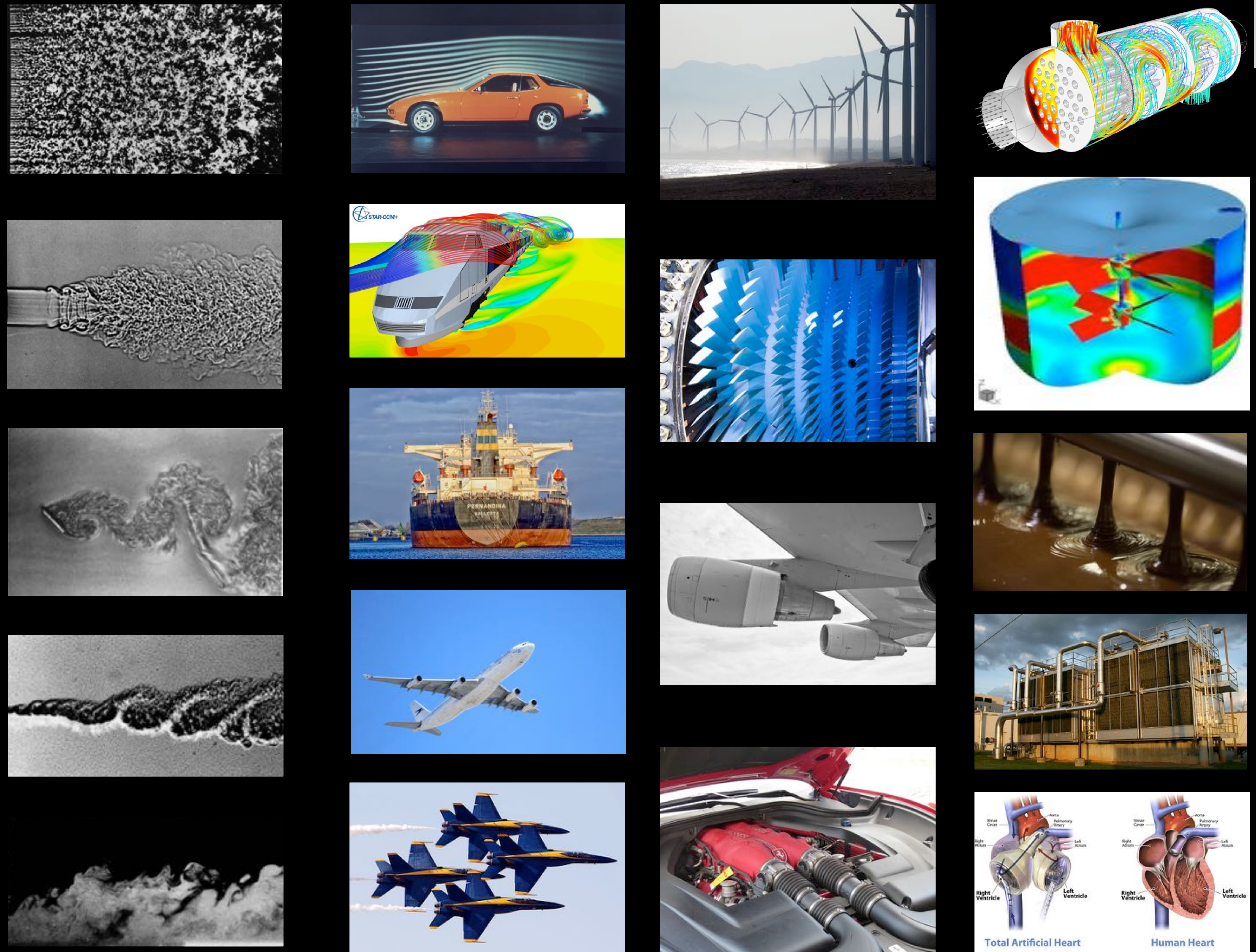


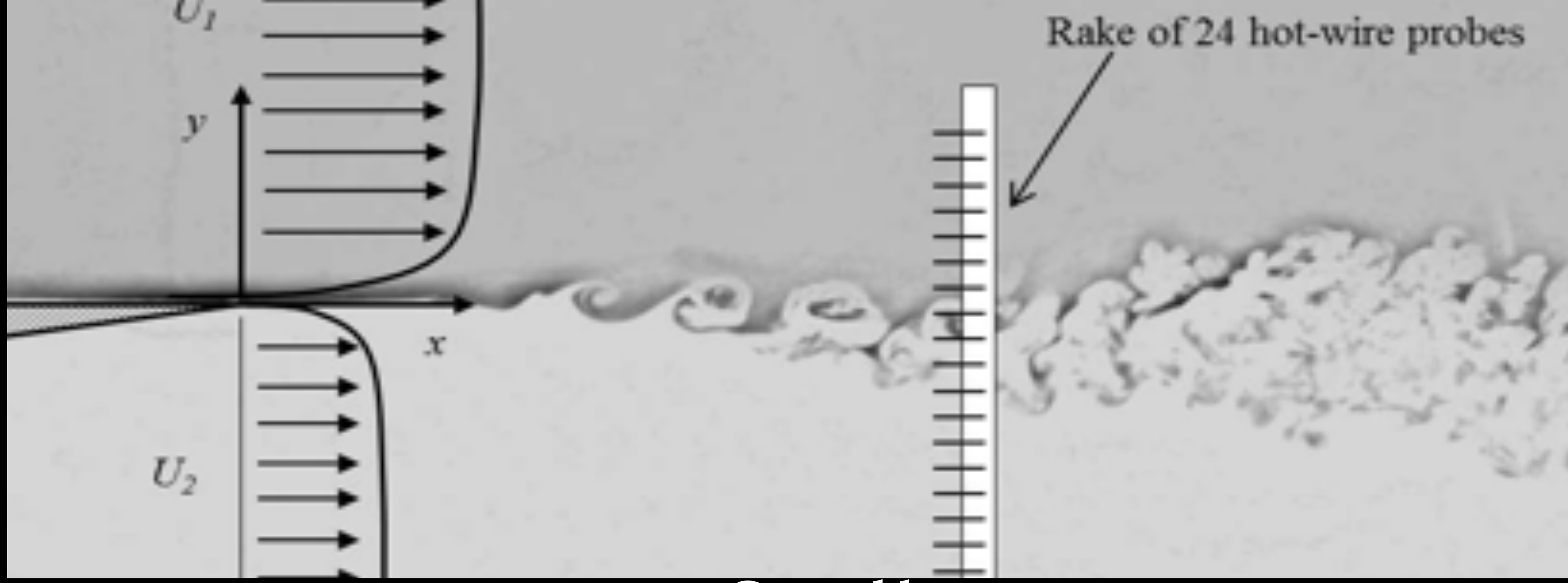
SLB, Noack, Koumoutsakos,
***Ann. Rev. Fluid Mech.* 2019**

Early Work:
Milano and Koumoutsakos,
***J. Comp. Phys.* 2002**

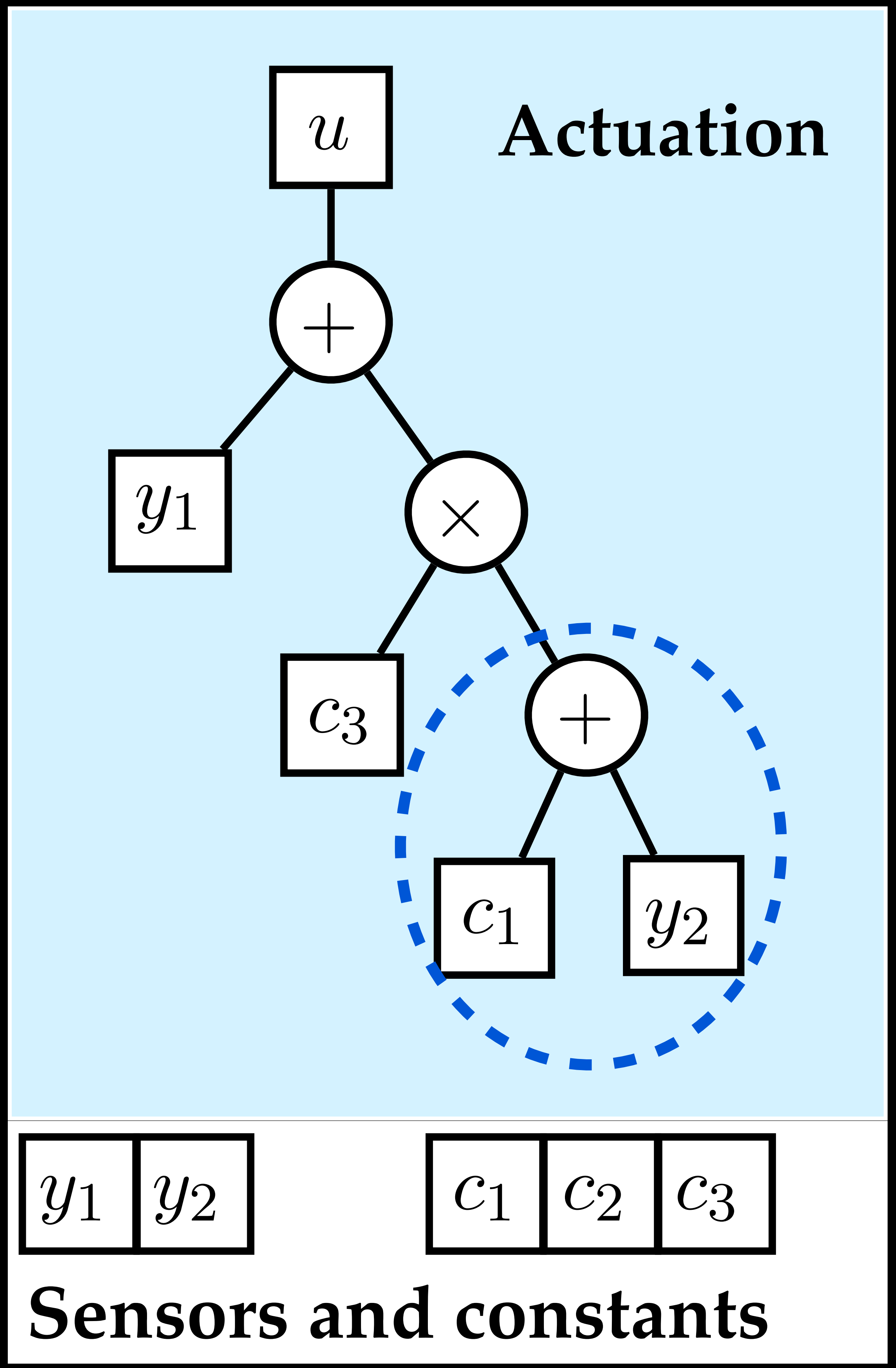
FLOW CONTROL

SLB, Noack, *AMR*, 2015
Duriez, SLB, Noack, Springer *2016*



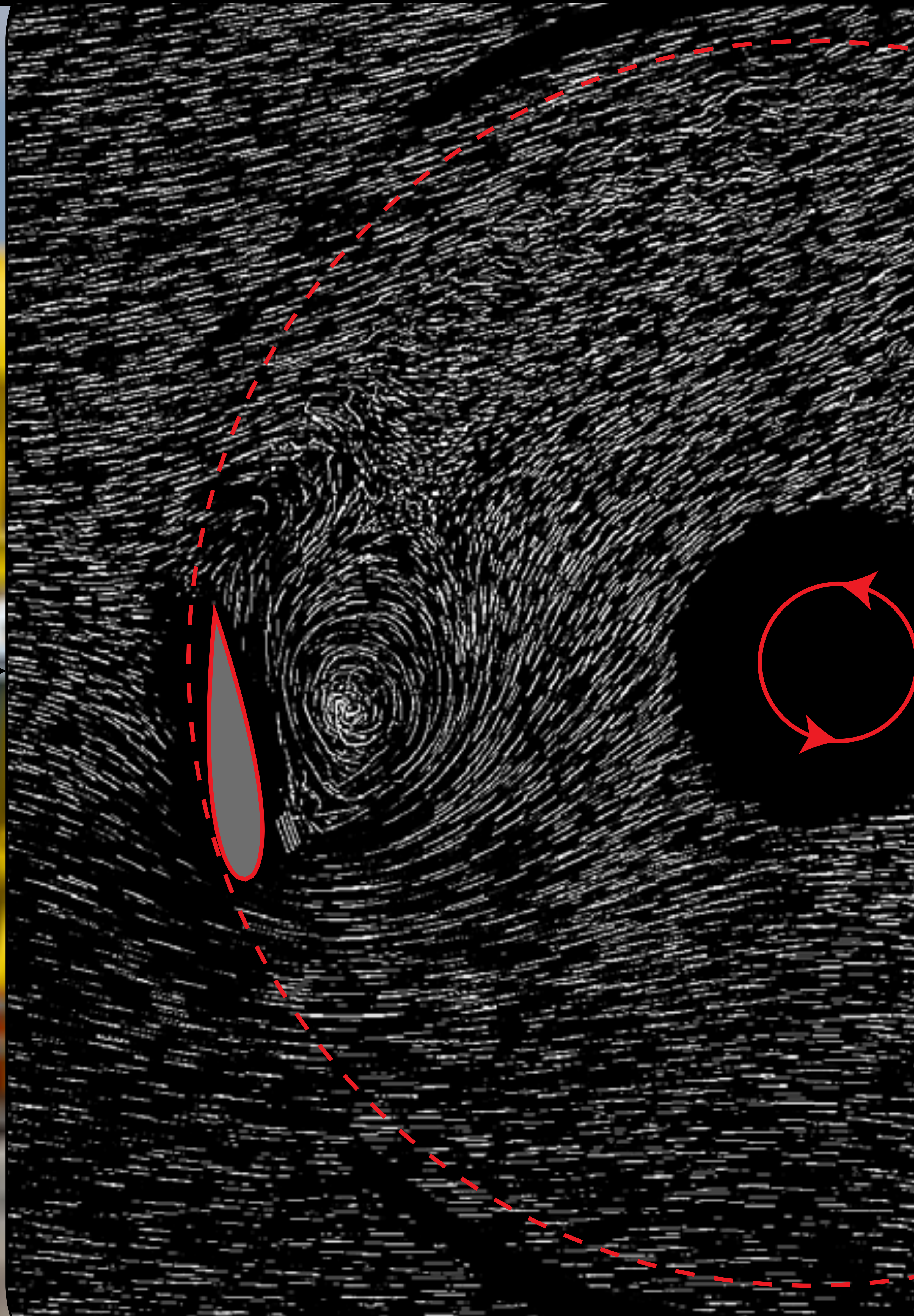


Control law



59% Power increase in lab-scale cross-flow turbine experiment using gradient simplex optimization

Nature Energy, 2017
Strom, SLB, Polagye



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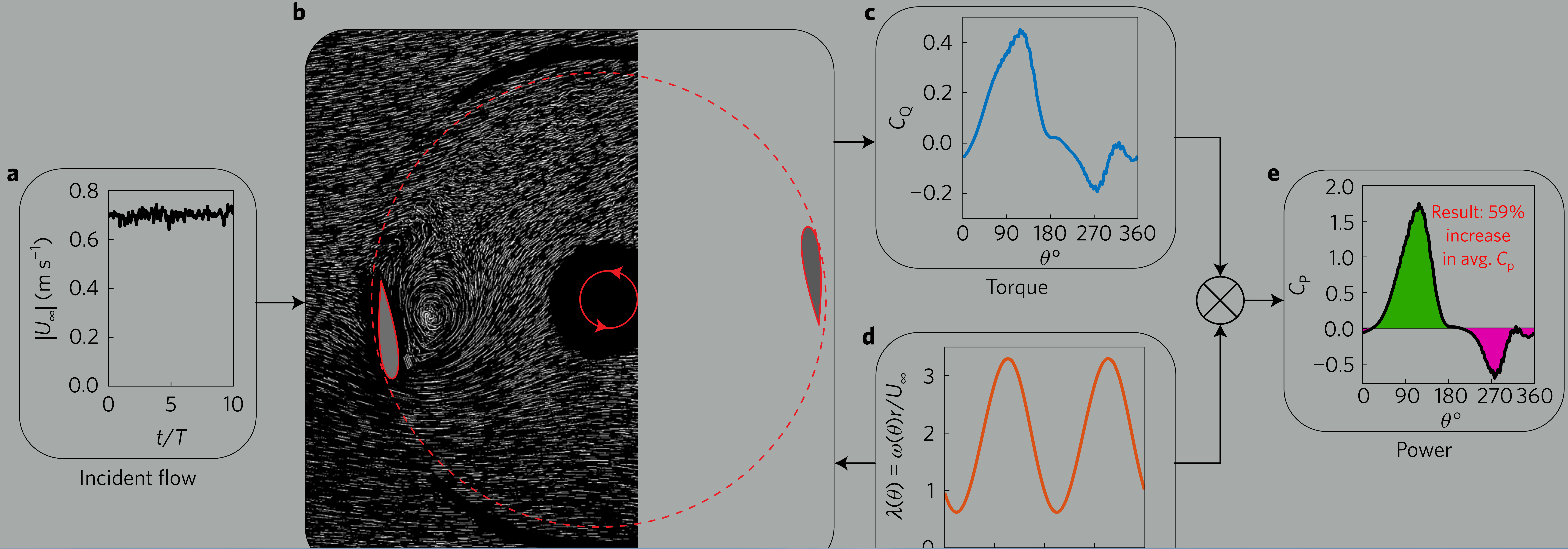

Governing equations are TOO COMPLEX to work with:

- Discover Reduced Order Models with machine learning

Dynamics are NONLINEAR and HIGH-DIMENSIONAL:

- Coordinate transformations to linearize dynamics
- Patterns facilitate sparse measurements

Proposed approach:

- Learn physics from data: interpretable & generalizable
- Respect known, or partially known, physics

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BIO-INSPIRED

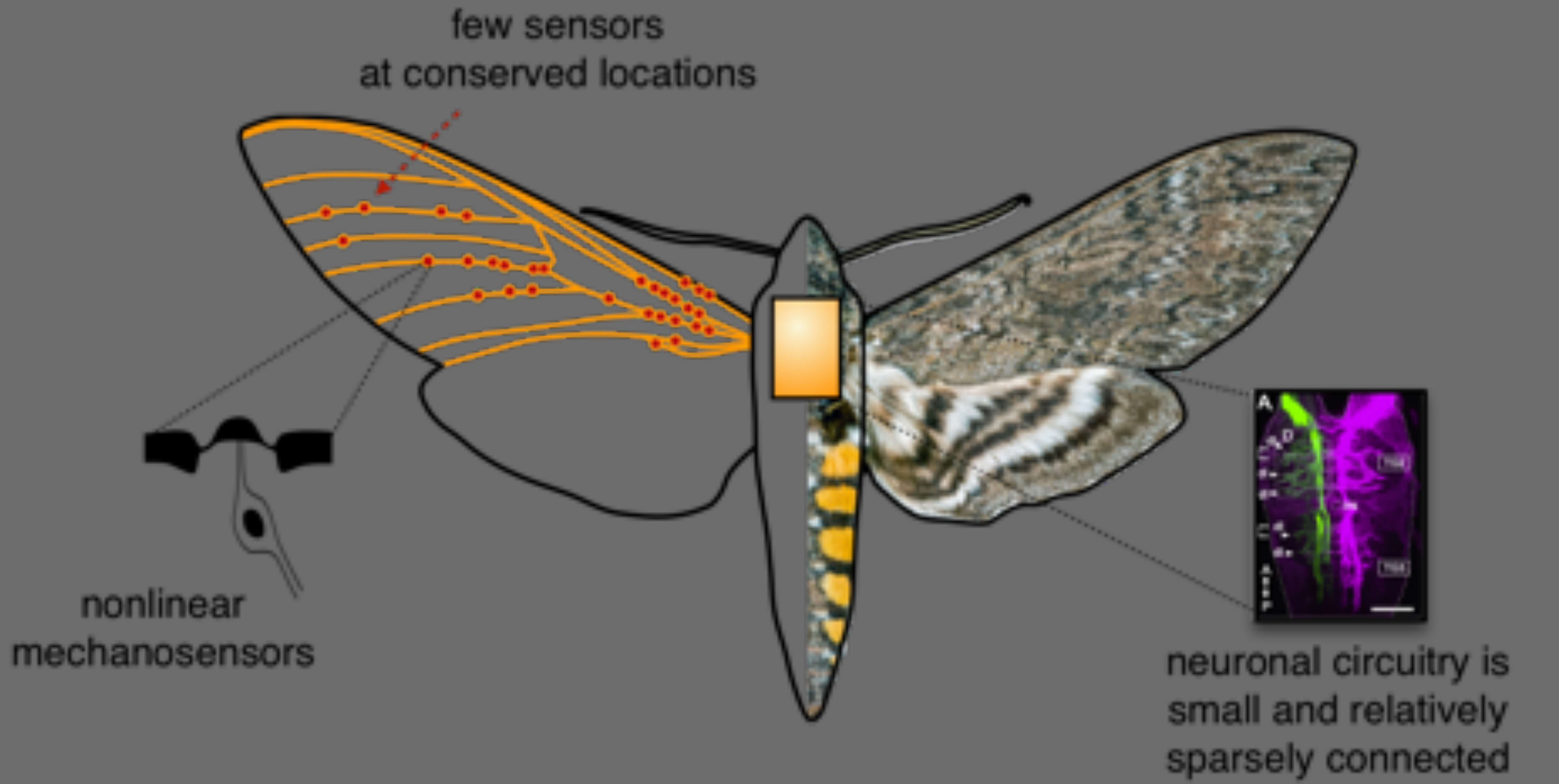
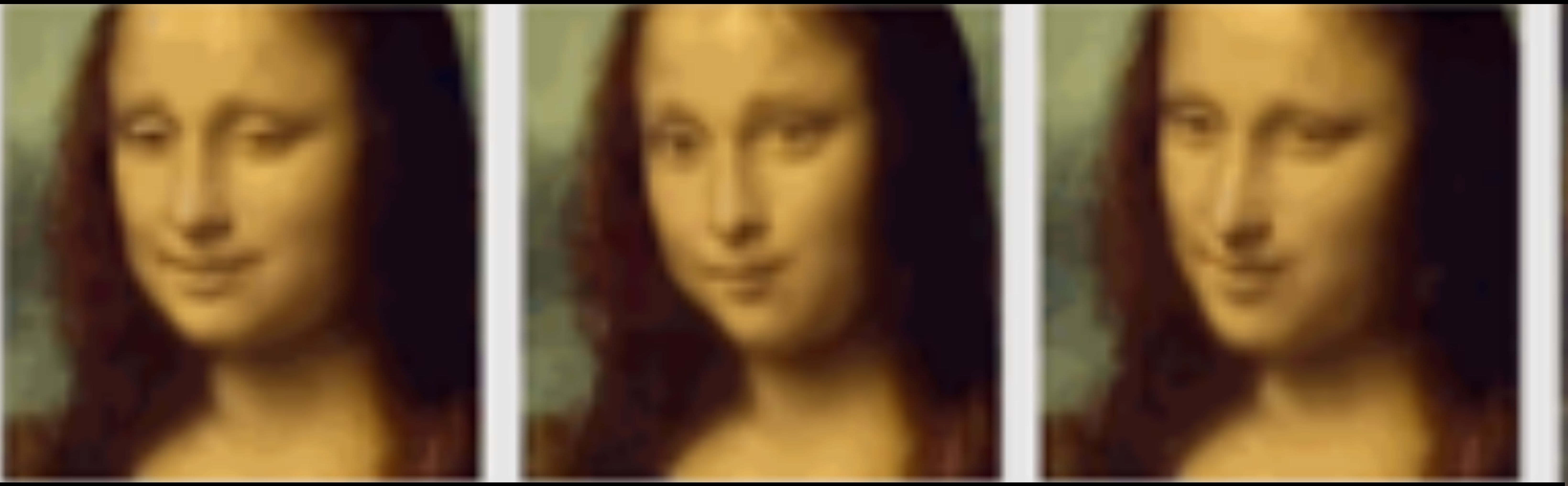


diagram adapted from Ali Weber

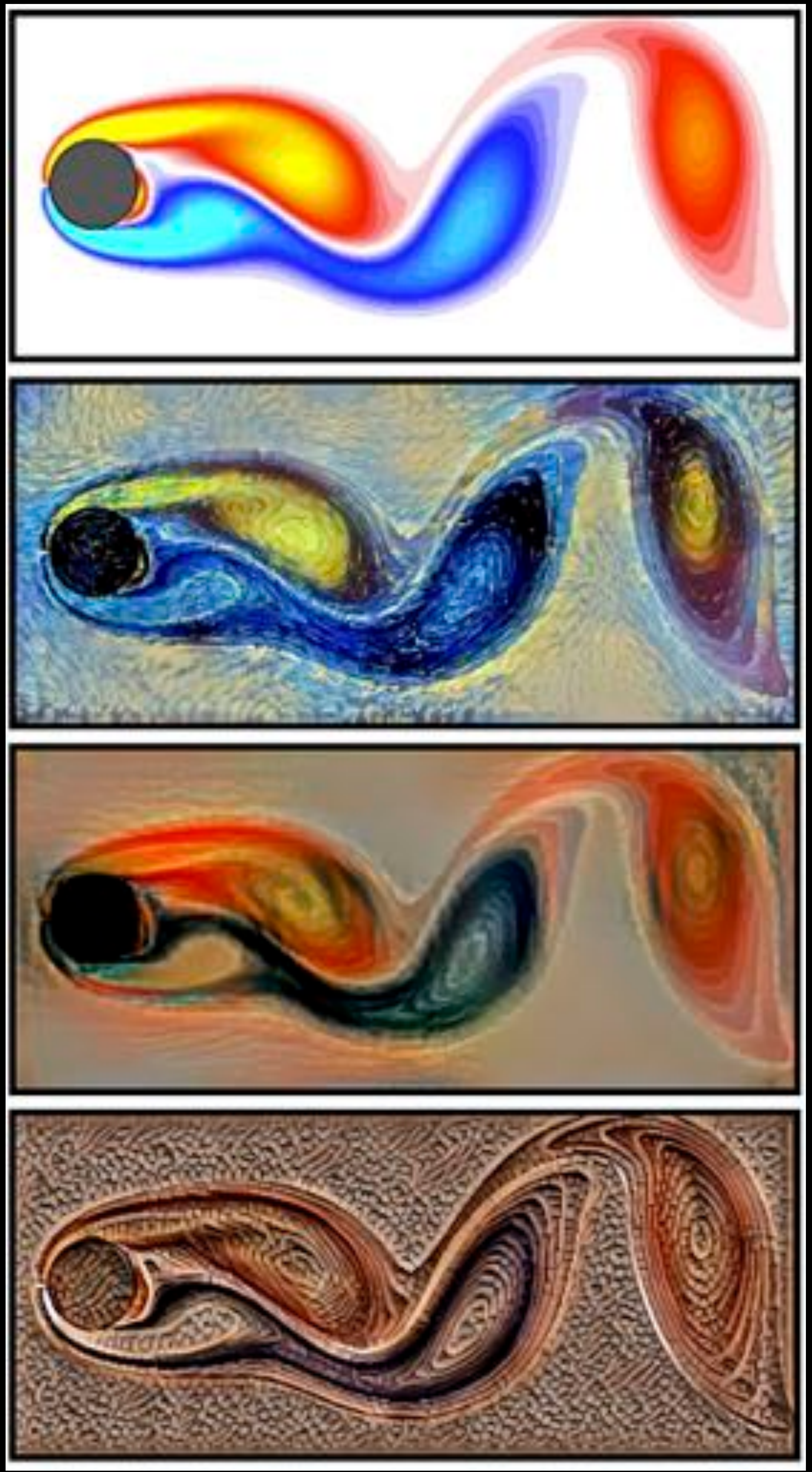
anatomy adapted from Ando et al. 2011.


ACTUATION
(Data In)
MRI Hyper-Sensed Environmentally Controlled Wind Tunnel
SENSING
(Data Out)
Wind speed, profile
Chemical source
Projectors
Fluid Environment
PIV (flow field)
Chemical sensors
Anemometer
Coupled
Feedback
Linear actuators
Blowing/Suction
etc...
Interacting Body
VICON motion
Force transducer
Neural recordings
Controller
Model-Based
State Estimation
Sensory Fusion,
Compressed
Sensing



Samsung AI Center and Skolkovo Institute of Science and Technology

Deep dream of Arcimbaldo's *La Primavera*
By Calhoun Press



dreamscopeapp.com

Fluid Dynamics