

## 7 Statistics

### 7.1 Introduction

# Statistics in the context of CFD

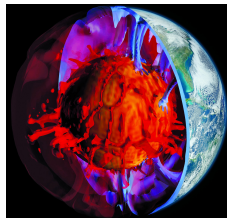
- ▶ Fluid flows are often **turbulent** (chaotic)
- ▶ A **statistical description** is therefore appropriate



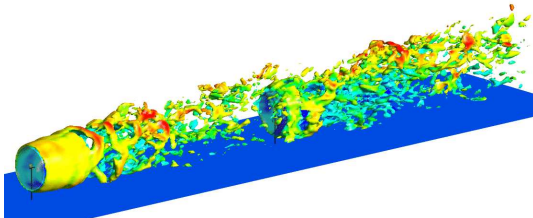
1



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4

1 – NASA, Langley Research Center, public domain

3 – GEOFLOW, ESA ([www.esa.int](http://www.esa.int))

2 – NREL ([www.nrel.gov](http://www.nrel.gov))

4 – NeSI ([www.nesi.org.nz](http://www.nesi.org.nz))

# First documented observation of turbulence

**Leonardo da Vinci** (1452–1519)



*Observe the motion of the surface of the water, which resembles that of hair, which has two motions, of which one is caused by the weight of the hair, the other by the direction of the curls; thus the water has eddying motions, one part of which is due to the principal current, the other to random and reverse motion.*<sup>1</sup>

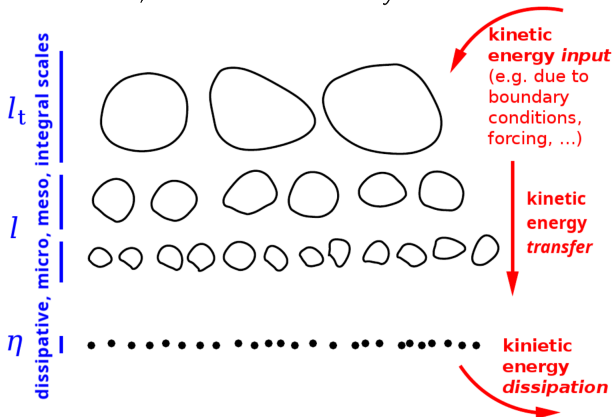
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<sup>1</sup>J. L. Lumley, "Some comments on turbulence", *Phys. Fluids A*, 1997, 4:203–211.

# A modern view on turbulence phenomenology

**Richardson<sup>2</sup>** (1922) – description of the energy cascade

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

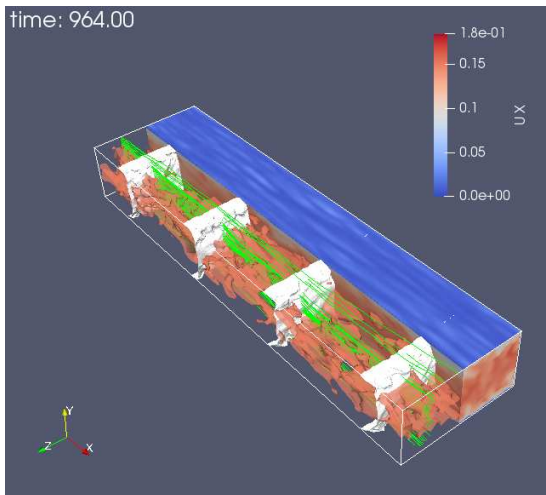


after: J. Fröhlich, TU Dresden

<sup>2</sup>L. F. Richardson, *Weather prediction by numerical process*, Cambridge, 1922.

# A canonical case: CFD simulation of turbulent channel flow

## Large-eddy simulation (LES) with WALE turbulence model using OpenFOAM



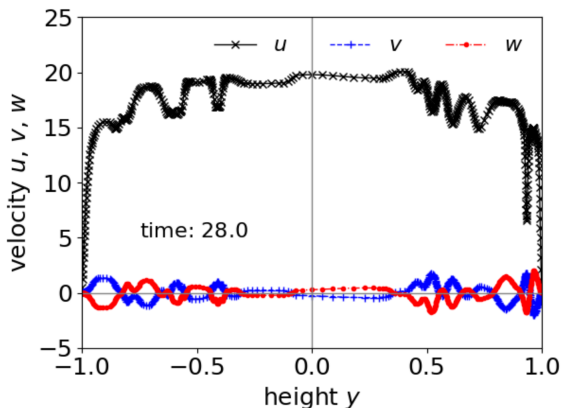
Video in Moodle:

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*Statistical turbulence modeling aims to predict the large-scale flow. Statistical properties are assumed for the small scales, e.g., based on the Richardson cascade!*

# Stochastic modeling of turbulent channel flow

## One-dimensional turbulence (ODT) simulation



Momentary flow profiles  
 $u(y, t)$ ,  $v(y, t)$ ,  $w(y, t)$

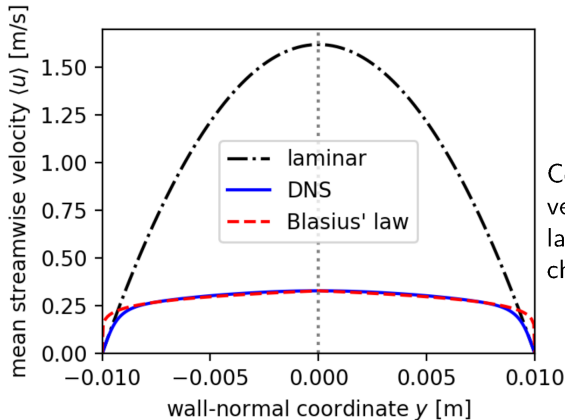
Video in Moodle:

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*Stochastic turbulence modeling* aims to reproduce chaotic fluctuations.  
This requires random numbers sampled from a random process!

# Mean velocity profiles for channel flow

- ▶ The *fully-developed* turbulent flow is **statistically stationary**
- ▶ Averaging yields the **mean streamwise velocity**  $\langle u \rangle$



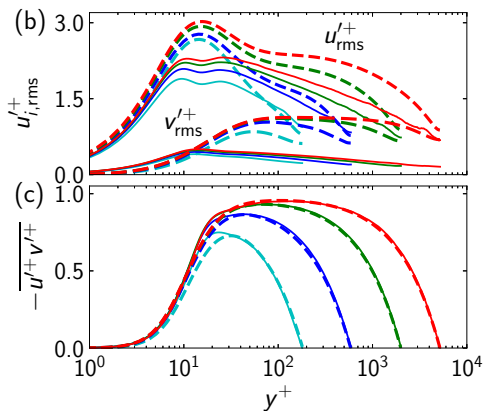
Comparison of mean velocity profiles in laminar and turbulent channel flow





# Standard deviation $u'_{i,\text{rms}}$ and cross-correlation $\overline{u'v'}$ of velocity fluctuations across the boundary layer

$$u'_{i,\text{rms}} = \sqrt{u_i'^2}$$



- **ODT:** M. Klein & H. Schmidt (2021) *STAB/DGLR Symposium 2020, NNFM* **151**:47–57
- **DNS:** M. Lee & R.D. Moser (2015) *J. Fluid Mech.* **774**:395–415

## 7 Statistics

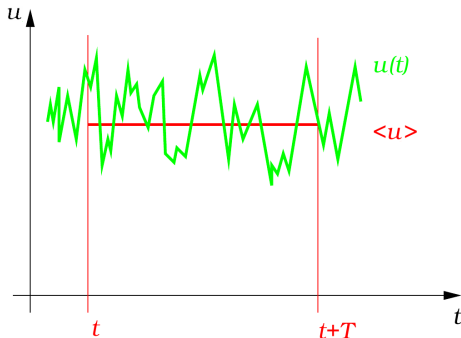
### 7.2 Definitions

# Statistical description of turbulent flows

Separation of flow variables, for example, the velocity vector  $u_i$ , into the mean  $\langle u_i \rangle$  and the *fluctuations*  $u'_i$  around the mean

$$u_i = \langle u_i \rangle + u'_i$$

**Reynolds decomposition**



after: N. Adams, TU Munich

## ► Temporal average

$$\langle u_i \rangle_t = \frac{1}{T} \int_t^{t+T} u_i(\mathbf{x}, \hat{t}) d\hat{t}$$

## ► Spatial average

$$\langle u_i \rangle_V = \frac{1}{V} \int_V u_i(\hat{\mathbf{x}}, t) d\hat{V}$$

## ► Ensemble average

$$\langle u_i \rangle_N = \frac{1}{N} \sum_{n=1}^N u_i^{(n)}(\mathbf{x}, t)$$

# Mean

- ▶ Consider a discrete sample  $\{x_1, x_2, x_3, \dots, x_i, \dots, x_N\}$  of  $N$  values in time, space, or due to an ensembles of different realizations
- ▶ The **mean value**  $\bar{x}$  is given by the arithmetic average

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

- ▶ This is the *first statistical moment* of the distribution of the  $x_i$

# Variance and standard deviation

- ▶ The **fluctuation variance**  $\sigma^2$  is obtained with unbiased estimator

$$\sigma^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2$$

N.B.: Why ' $N - 1$ '? Because for only one value,  $N = 1$ , there is no variance. Hence,  $\sigma^2 = \frac{0}{0} = \text{n.d.}$

- ▶ The **standard deviation of the fluctuations**  $\sigma$  is given by

$$\sigma = \sqrt{\sigma^2}$$

- ▶ For large  $N \gg 1$ ,  $\sigma^2$  can be obtained as difference of the *second* and *first statistical moment squared*

$$\sigma^2 = \left( \frac{1}{N} \sum_{i=1}^N x_i^2 \right) - \bar{x}^2$$

N.B.:

$$\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2 = \underbrace{\frac{1}{N-1} \sum_{i=1}^N (x_i^2 - 2\bar{x}x_i + \bar{x}^2)}_{\simeq N} = \frac{1}{N} \sum_{i=1}^N x_i^2 - \underbrace{2\bar{x} \frac{1}{N} \sum_{i=1}^N x_i}_{-2\bar{x}^2} + \underbrace{\frac{1}{N} \sum_{i=1}^N \bar{x}^2}_{\bar{x}^2} = \frac{1}{N} \sum_{i=1}^N x_i^2 - \bar{x}^2$$

# Higher-order statistical moments

- ▶ The equation for the mean of a discrete sample can be generalized to arbitrary statistical moments  $q$

$$\overline{x^q} = \frac{1}{N} \sum_{i=1}^N x_i^q$$

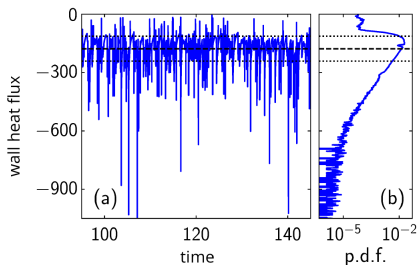
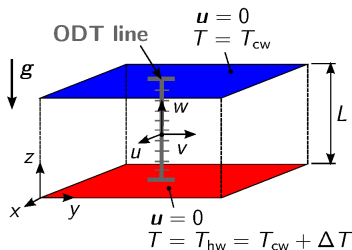
- ▶  $q > 2$  denotes **higher-order statistical moments**
- ▶ Correspondingly, higher-order statistical moments of the **fluctuations** are given by the unbiased estimator

$$\overline{\sigma^q} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^q$$

- ▶ This is used to define additional statistical quantities, such as the *skewness* for  $q = 3$  or *flatness (kurtosis)* for  $q = 4$ , giving additional information about the distribution (PDF) of the  $x_i$

# Histogram and probability density function (PDF) I

- ▶ The **histogram** gives the *absolute number*  $n_k$  of values  $x_i$  that fall within predefined intervals (bins)  $[b_k, b_{k+1}]$
- ▶ The **probability density function (PDF)** gives the *relative number*  $\frac{n_k}{N}$  of values  $x_i$  per bin of size  $\Delta b_k = b_{k+1} - b_k$ , that is,  $p_k = \frac{n_k}{N \cdot \Delta b_k}$



Discrete time series (a) and PDF (b) of wall heat flux obtained with a stochastic model for thermal convection. M. Klein, ICTAM 2020+1.

— raw data    -- mean    ... mean  $\pm$  standard deviation

# Histogram and probability density function (PDF) II

- ▶ Algorithmically,  $n_k$  is obtained by counting all  $x_i$  that fulfill  $b_k \leq x_i \leq b_{k+1}$  for given  $k$ . This is repeated for all  $k$ .  
→ Use *nested loops*:  $k$  goes to the outer and  $i$  to the inner loop
- ▶ Note that  $k = 1, 2, \dots, M$  and  $i = 1, 2, \dots, N$ , where  $N \gg M \gg 1$  for a reasonably populated and resolved histogram that *approximates* the underlying distribution (the 'true' PDF)
- ▶ Technically, the PDF is the *normalized histogram* in the limit  $N, M \rightarrow \infty$  with  $\max_k(\Delta b_k) \rightarrow 0$



# Obtaining arbitrary statistical moments with the PDF

- ▶ The PDF is the normalized histogram in the infinitesimal limit
- ▶ Adopting infinitesimal calculus notation, we have

discrete variable  $x_i \rightarrow$  continuous variable  $x$

discrete bin size  $\Delta b_k \rightarrow$  infinitesimal interval  $dx$

discrete PDF  $p_k \rightarrow$  continuous PDF  $p(x)$

- ▶ Any **statistical moment of a continuous variable** is obtained from

$$\overline{x^q} = \int_{-\infty}^{+\infty} x^q p(x) dx$$

The PDF contains all statistical information for the considered sample.  
This includes the mean and details of fluctuations.

# Retrieving low-order moments from the PDF

- Normalization follows from  $q = 0$ , that is, the integral of the PDF must be equal to one

$$1 = \int_{-\infty}^{+\infty} p(x) dx$$

- The mean is obtained for  $q = 1$  as

$$\bar{x} = \int_{-\infty}^{+\infty} x p(x) dx$$

- The variance is obtained for  $q = 2$  as

$$\begin{aligned}\sigma^2 &= \int_{-\infty}^{+\infty} (x - \bar{x})^2 p(x) dx = \int_{-\infty}^{+\infty} (x^2 - 2\bar{x}x + \bar{x}^2) p(x) dx \\ &= \int_{-\infty}^{+\infty} x^2 p(x) dx - 2\bar{x} \int_{-\infty}^{+\infty} x p(x) dx + \bar{x}^2 \int_{-\infty}^{+\infty} p(x) dx \\ &= \int_{-\infty}^{+\infty} x^2 p(x) dx - \bar{x}^2 \int_{-\infty}^{+\infty} p(x) dx = \overline{x^2} - \bar{x}^2\end{aligned}$$

## Extension to two and more variables

- ▶ Consider time series of two variables  $x(t)$  and  $y(t)$  that may be represented by discrete samples  $(x_i, y_i)$  with  $i = 1, 2, \dots, N$
- ▶ The PDF will now depend on two variables, it is called the **joint probability density function (JPDF)**

$$P(x, y) \quad \text{such that} \quad 1 = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} P(x, y) dx dy$$

- ▶ The statistical moments now also encompass **cross-correlations** for  $r > 0$  and  $s > 0$

$$\overline{x^r y^s} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^r y^s P(x, y) dx dy$$

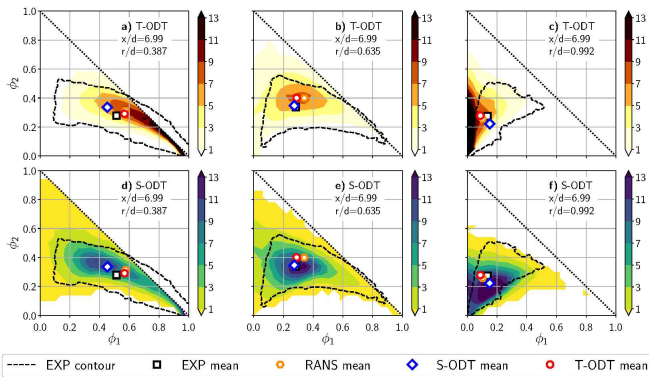
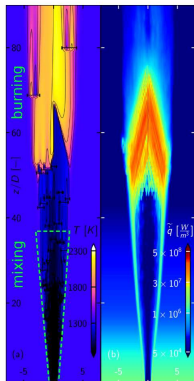
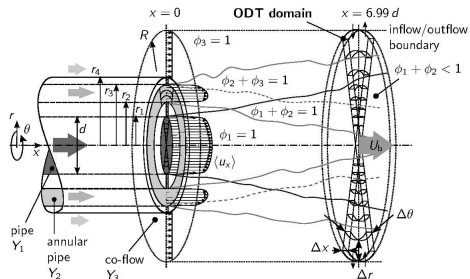
- ▶ **Auto-correlations**  $\overline{x^r}$  and  $\overline{y^s}$  are obtained from the marginal PDFs  $p_1(x)$  and  $p_2(y)$  in the case of  $s = 0$  and  $r = 0$ , respectively, since

$$p_1(x) = \int_{-\infty}^{+\infty} P(x, y) dy \quad p_2(y) = \int_{-\infty}^{+\infty} P(x, y) dx$$

# JPDFs of two-scalar mixing in a round jet

M. Klein *et al.*, TSFP12, 2022

T. Starick *et al.*, TSFP11, 2019



## 7 Statistics

### 7.3 Hands-on applications

# Statistical analysis and prediction of dynamical systems

## Diagnostics

- ▶ Analysis of fluid flows in CFD (DNS, LES) and measurements
- ▶ Analysis of the Lorenz system

→ *Exercise 7*

## Prediction

- ▶ Formulation of Reynolds-averaged Navier–Stokes (RANS) equations
- ▶ Formulation of statistical turbulence models in RANS and LES
- ▶ Formulation of PDF transport models for CFD applications

# Statistical analysis of random processes

- ▶ Analysis of random processes (like throw of a dice)
- ▶ Analysis of random walks (like Brownian motion, tracer dispersion)
- ▶ Quality assurance of random number generators
- ▶ ...

→ *Exercise 8*

# Keywords

- ▶ Statistics of turbulent fluid flows
- ▶ Mean and variance
- ▶ Higher-order moments
- ▶ Probability density function (PDF)