

**New Challenges in Turbulence Research VI**  
**Les Houches, February 2021**

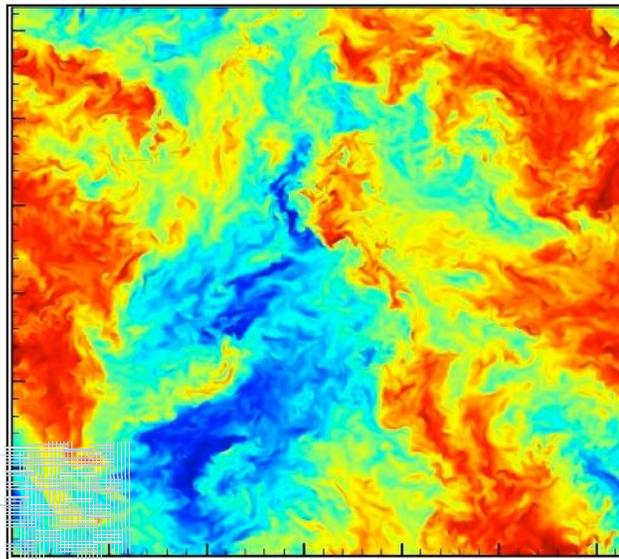
# **Large Eddy Simulations of Turbulence and Insights generated regarding Wind Energy**

Charles Meneveau  
Johns Hopkins University

# Coarse-graining - Large-Eddy-Simulation (LES):

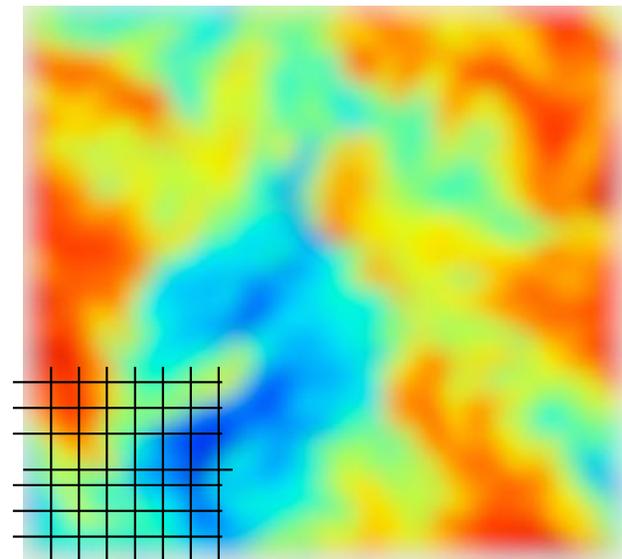
Coarse-graining for more affordable simulations

$$u_1(x, y, z_0, t_0)$$



$4 \times 10^9$   
d.o.f.

$$\tilde{u}_1(x, y, z_0, t_0)$$

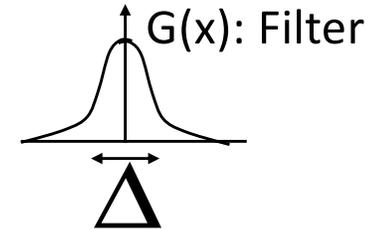


$10^5$   
d.o.f.

# Large-eddy-simulation (LES) and filtering:

## N-S equations:

$$\frac{\partial u_j}{\partial t} + \frac{\partial u_k u_j}{\partial x_k} = -\frac{\partial p}{\partial x_j} + \nu \nabla^2 u_j \quad \frac{\partial u_j}{\partial x_j} = 0$$

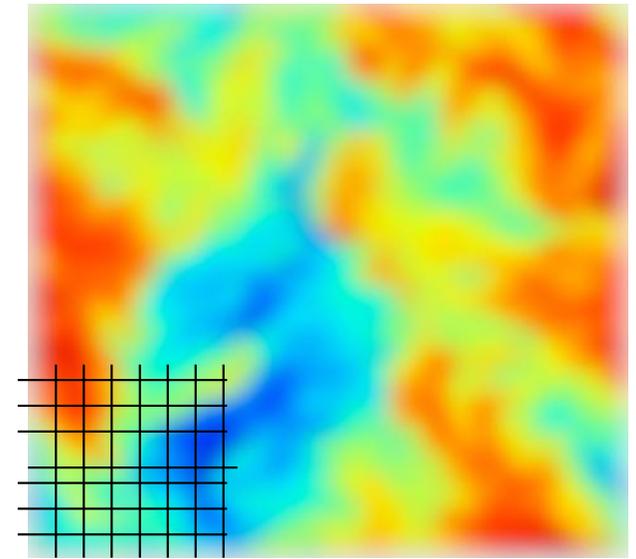


$$\tilde{u}_1(x, y, z_0, t_0)$$

## Filtered N-S equations:

$$\frac{\partial \tilde{u}_j}{\partial t} + \frac{\partial \widetilde{u_k u_j}}{\partial x_k} = -\frac{\partial \tilde{p}}{\partial x_j} + \nu \nabla^2 \tilde{u}_j$$

$$\frac{\partial \tilde{u}_j}{\partial t} + \tilde{u}_k \frac{\partial \tilde{u}_j}{\partial x_k} = -\frac{\partial \tilde{p}}{\partial x_j} + \nu \nabla^2 \tilde{u}_j - \frac{\partial}{\partial x_k} \tau_{jk}$$



where SGS stress tensor is:

$$\tau_{ij} = \widetilde{u_i u_j} - \tilde{u}_i \tilde{u}_j$$

# Most common modeling approach: eddy-viscosity

$$\tau_{ij}^d = -\nu_{sgs} \left( \frac{\partial \tilde{u}_i}{\partial x_j} + \frac{\partial \tilde{u}_j}{\partial x_i} \right) = -2\nu_{sgs} \tilde{S}_{ij}$$

$$\nu_{sgs} = l \times vel \sim \Delta \times (\Delta |\tilde{S}|)$$

$$\nu_{sgs} = (c_s \Delta)^2 |\tilde{S}|$$

$c_s$ : “Smagorinsky coefficient”

## HISTORY: 1960s, 1970s

- J Smagorinsky
- DK Lilly
- J Deardorff

# Effects of $\tau_{ij}$ upon resolved motions: Energetics (kinetic energy):

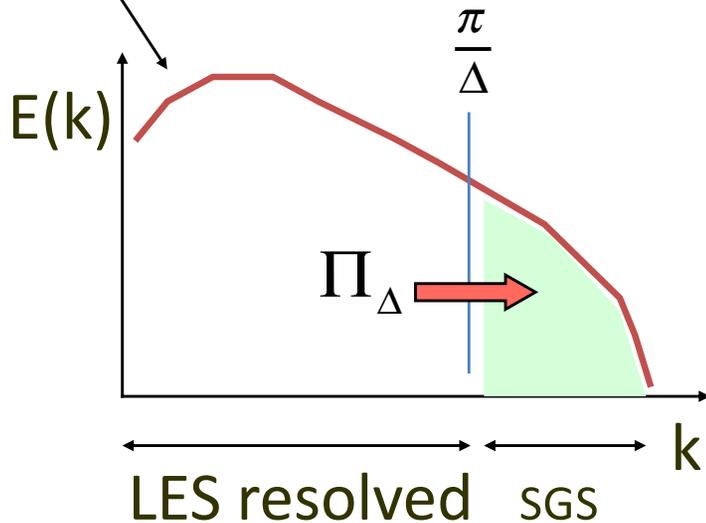
$$\frac{\partial \frac{1}{2} \tilde{u}_j \tilde{u}_j}{\partial t} + \tilde{u}_k \frac{\partial \frac{1}{2} \tilde{u}_j \tilde{u}_j}{\partial x_k} = -\frac{\partial}{\partial x_j} (\dots) - 2\nu \tilde{S}_{jk} \tilde{S}_{jk} - (-\tau_{jk} \tilde{S}_{jk})$$

$$\tilde{S}_{ij} = \frac{1}{2} \left( \frac{\partial \tilde{u}_i}{\partial x_j} + \frac{\partial \tilde{u}_j}{\partial x_i} \right)$$

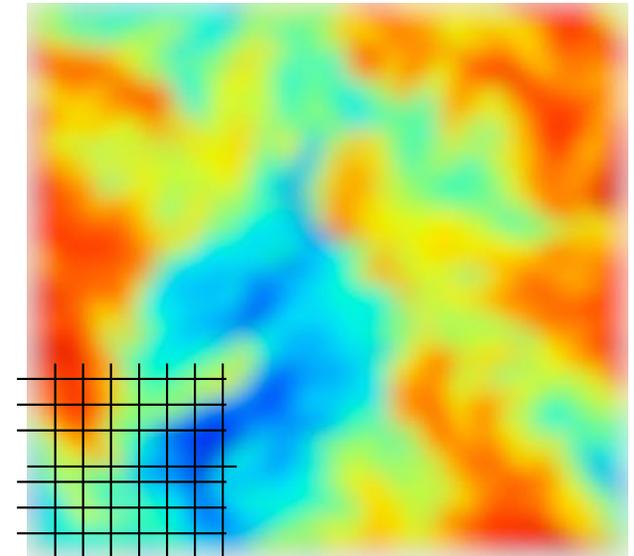
$$\Pi_{\Delta} = -\langle \tau_{jk} \tilde{S}_{jk} \rangle$$

**Inertial-range flux**

$$\varepsilon = \frac{u'^3}{L}$$



$$\tilde{u}_1(x, y, z_0, t_0)$$



$\Delta$

## Two-point structure of coarse-grained NS:

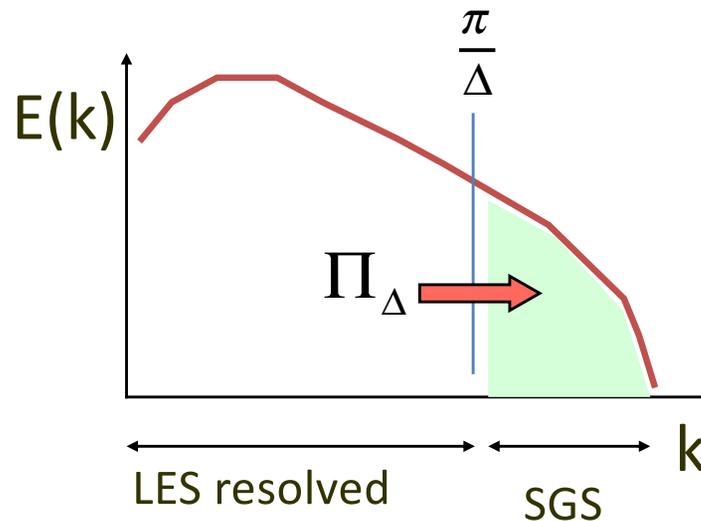
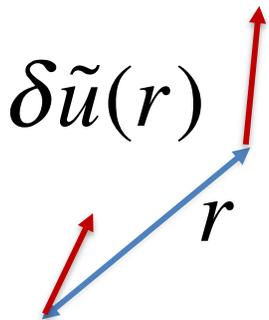
$$\frac{\partial \frac{1}{2} \tilde{u}_j \tilde{u}_j}{\partial t} + \tilde{u}_k \frac{\partial \frac{1}{2} \tilde{u}_j \tilde{u}_j}{\partial x_k} = -\frac{\partial}{\partial x_j} (\dots) - 2\nu \tilde{S}_{jk} \tilde{S}_{jk} - (-\tau_{jk} \tilde{S}_{jk})$$

$$\Pi_{\Delta} = -\langle \tau_{jk} \tilde{S}_{jk} \rangle$$

Similarly to von Karman-Howarth and Kolmogorov equations,  
For isotropic turbulence, in inertial range (CM PoF 1994):

“sufficient condition at  $r \gg \Delta$ : predict  $\Pi_{\Delta}$ ” correctly

$$\langle \delta \tilde{u}(r)^3 \rangle + 6 \langle \tau_{LL}(x) \delta \tilde{u}(r) \rangle = -\frac{4}{5} \Pi_{\Delta} r$$



$$\tau_{ij} = -2(c_s \Delta)^2 |\tilde{S}| \tilde{S}_{ij}$$

Simplest model that can  
“control” the “dissipation”

But how much is  $c_s$ ?

## Theoretical calibration of $c_s$ (D.K. Lilly, 1967) HIT:

$$\Pi_\Delta = \varepsilon = -\langle \tau_{ij} \tilde{S}_{ij} \rangle \quad \tau_{ij} = -2(c_s \Delta)^2 |\tilde{S}| \tilde{S}_{ij}$$

$$\varepsilon = c_s^2 \Delta^2 2 \langle |\tilde{S}| \tilde{S}_{ij} \tilde{S}_{ij} \rangle$$

$$\varepsilon \approx c_s^2 \Delta^2 2^{3/2} \langle \tilde{S}_{ij} \tilde{S}_{ij} \rangle^{3/2}$$

$$\langle \tilde{S}_{ij} \tilde{S}_{ij} \rangle = \frac{1}{2} \left\langle \frac{\partial \tilde{u}_i}{\partial x_j} \left( \frac{\partial \tilde{u}_i}{\partial x_j} + \frac{\partial \tilde{u}_j}{\partial x_i} \right) \right\rangle =$$

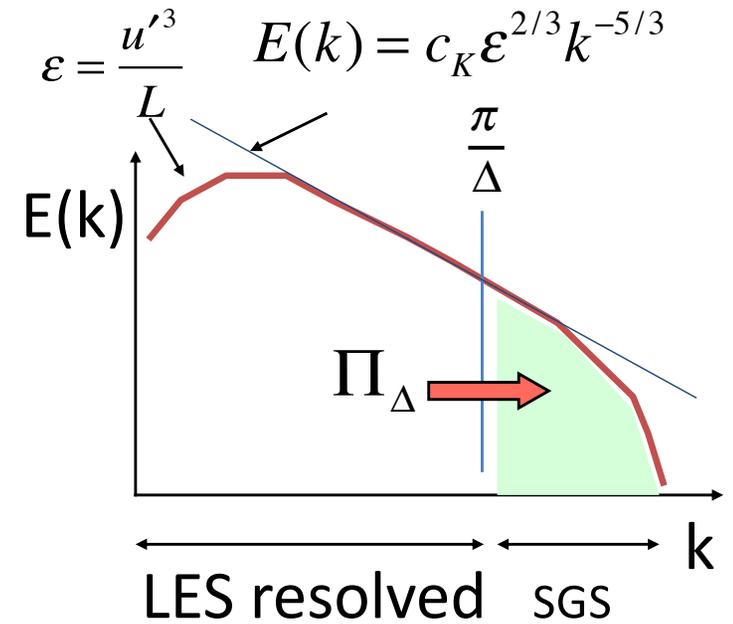
$$= \frac{1}{2} \iiint_{|\mathbf{k}| < \pi/\Delta} [k_j^2 \Theta_{ii}(\mathbf{k}) + k_i k_j \Theta_{ij}(\mathbf{k})] d^3 \mathbf{k} = \frac{1}{2} \iiint_{|\mathbf{k}| < \pi/\Delta} [k^2 \left( \frac{E(k)}{4\pi k^2} (\delta_{ii} - \frac{k^2}{k^2}) \right) + 0] d^3 \mathbf{k}$$

$$= c_K \varepsilon^{2/3} \frac{1}{2} \int_0^{\pi/\Delta} k^{-5/3+2} \frac{3-1}{4\pi k^2} 4\pi k^2 dk = c_K \varepsilon^{2/3} \int_0^{\pi/\Delta} k^{1/3} dk = c_K \varepsilon^{2/3} \frac{3}{4} \left( \frac{\pi}{\Delta} \right)^{4/3}$$

$$\varepsilon \approx c_s^2 \Delta^2 2^{3/2} \left( c_K \varepsilon^{2/3} \frac{3}{4} \left( \frac{\pi}{\Delta} \right)^{4/3} \right)^{3/2}$$

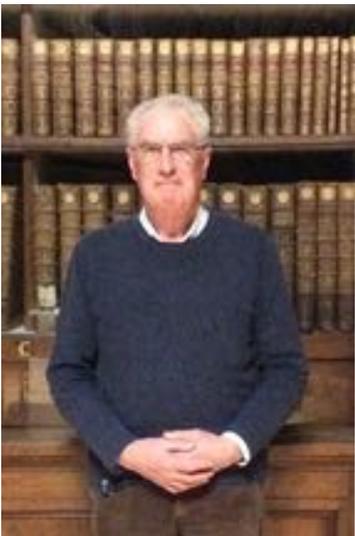
$$\Rightarrow 1 \approx c_s^2 \pi^2 \left( \frac{3c_K}{2} \right)^{3/2} \Rightarrow c_s = \left( \frac{3c_K}{2} \right)^{-3/4} \pi^{-1}$$

$$c_K = 1.6 \Rightarrow c_s \approx 0.16$$



# How to avoid “tuning” and case-by-case adjustments of model coefficient in LES?

## The Dynamic Model (30 years anniversary) (Germano et al. Physics of Fluids, 1991)



Massimo Germano  
(proposed G-identity)

### **A dynamic subgrid-scale eddy viscosity model**

Massimo Germano,<sup>a)</sup> Ugo Piomelli,<sup>b)</sup> Parviz Moin, and William H. Cabot  
*Center for Turbulence Research, Stanford, California 94305*

(Received 14 November 1990; accepted 7 March 1991)

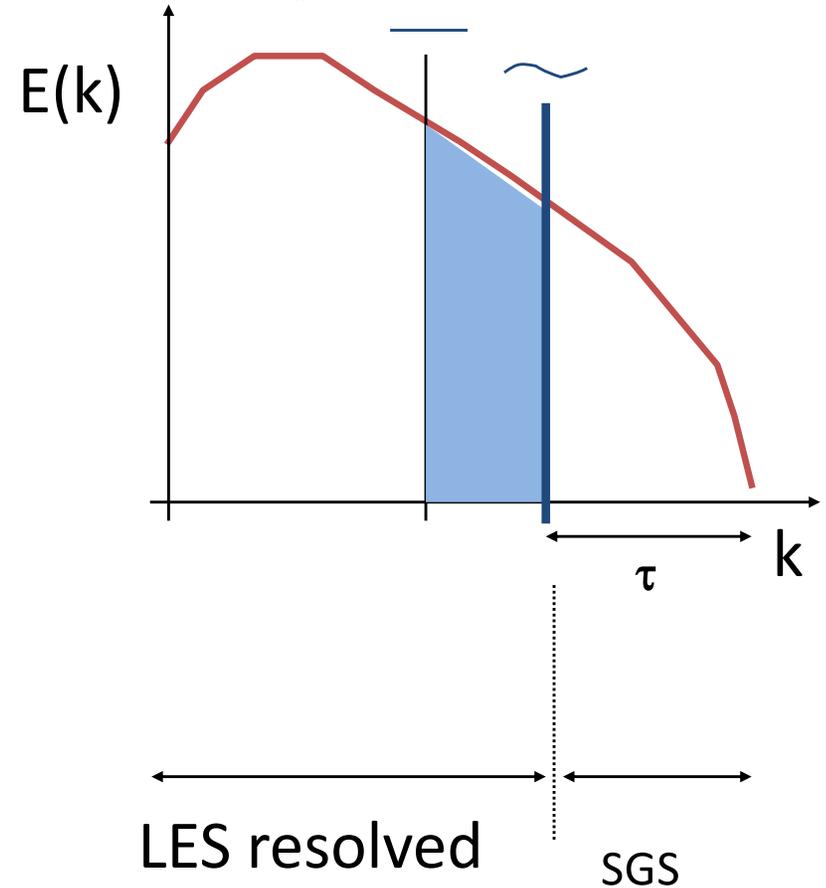
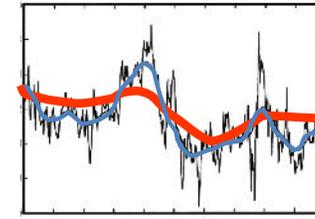
One major drawback of the eddy viscosity subgrid-scale stress models used in large-eddy simulations is their inability to represent correctly with a single universal constant different turbulent fields in rotating or sheared flows, near solid walls, or in transitional regimes. In the present work a new eddy viscosity model is presented which alleviates many of these drawbacks. The model coefficient is computed dynamically as the calculation progresses rather

# Germano identity and dynamic model

(Germano et al. 1991):

*Exact ("rare" in turbulence):*

$$\overline{\widetilde{u_i u_j}} - \widetilde{u_i} \widetilde{u_j} = \overline{u_i u_j} - \widetilde{u_i} \widetilde{u_j}$$



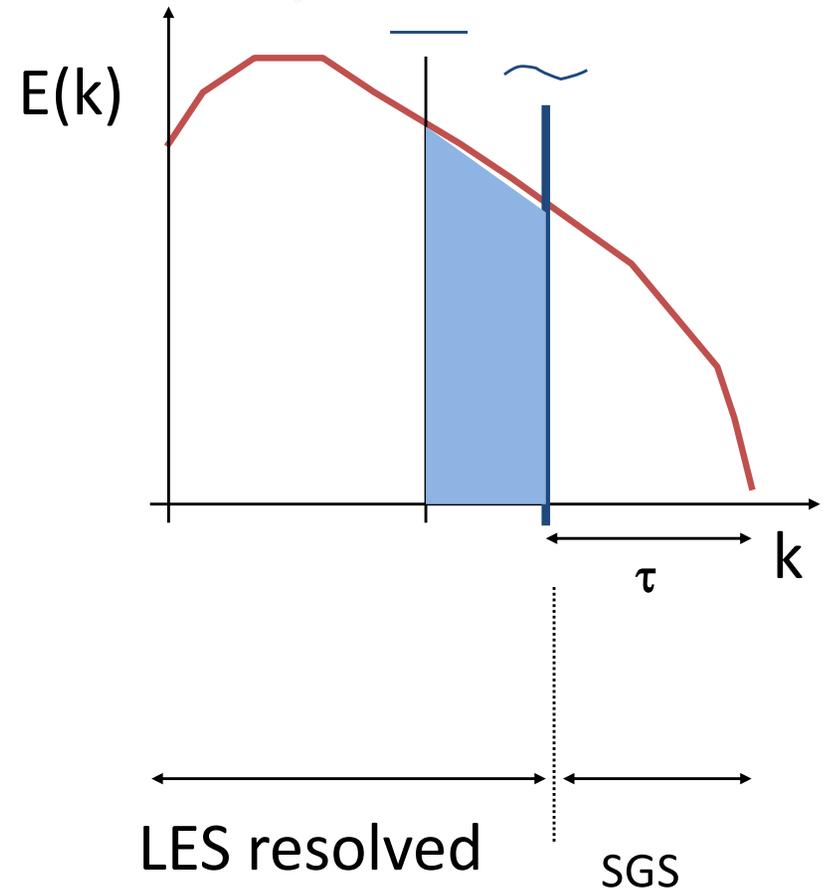
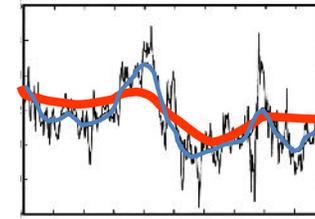
# Germano identity and dynamic model

(Germano et al. 1991):

*Exact ("rare" in turbulence):*

$$\overline{\widetilde{u}_i \widetilde{u}_j} - \widetilde{\overline{u}_i \overline{u}_j} = \overline{\widetilde{u}_i \widetilde{u}_j} - \widetilde{\overline{u}_i \overline{u}_j} + \widetilde{\overline{u}_i \overline{u}_j} - \widetilde{\overline{u}_i \overline{u}_j}$$

$$T_{ij} = \bar{\tau}_{ij} + L_{ij}$$



# Germano identity and dynamic model

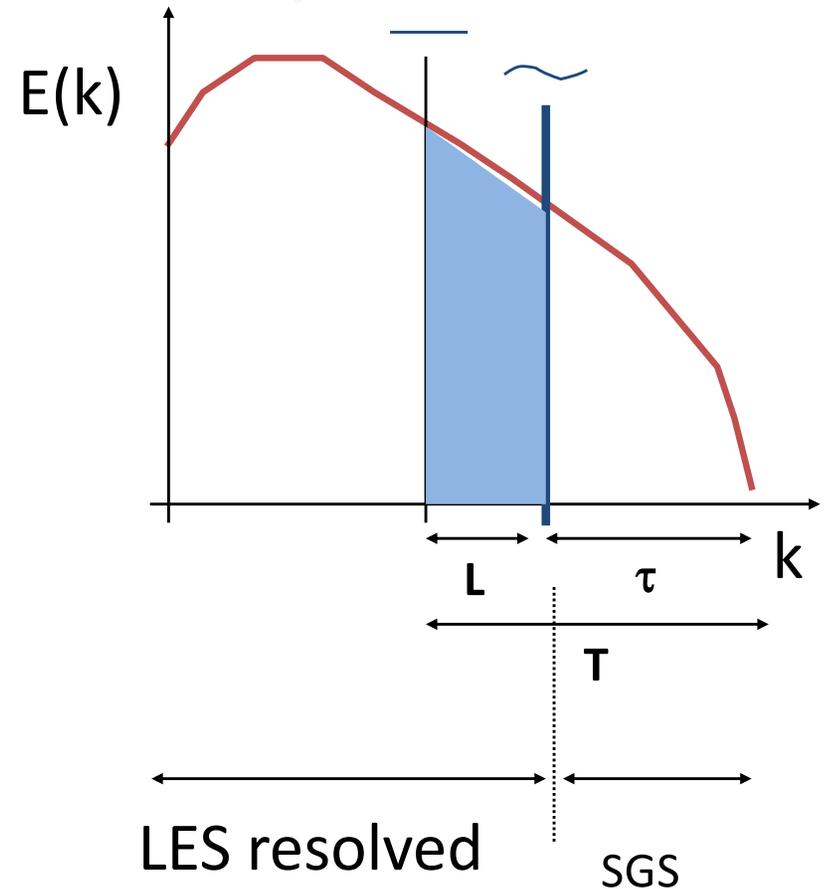
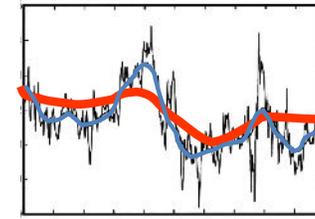
(Germano et al. 1991):

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$$T_{ij} = \bar{\tau}_{ij} + L_{ij}$$

$$L_{ij} - (T_{ij} - \bar{\tau}_{ij}) = 0$$



# Germano identity and dynamic model

(Germano et al. 1991):

Exact (“rare” in turbulence):

$$\overline{\widetilde{u}_i \widetilde{u}_j} - \widetilde{\overline{u}_i \overline{u}_j} = \overline{\widetilde{u}_i \widetilde{u}_j} - \widetilde{\overline{u}_i \overline{u}_j} + \widetilde{\overline{u}_i \overline{u}_j} - \widetilde{\overline{u}_i \overline{u}_j}$$



$$T_{ij} = \tau_{ij} + L_{ij}$$

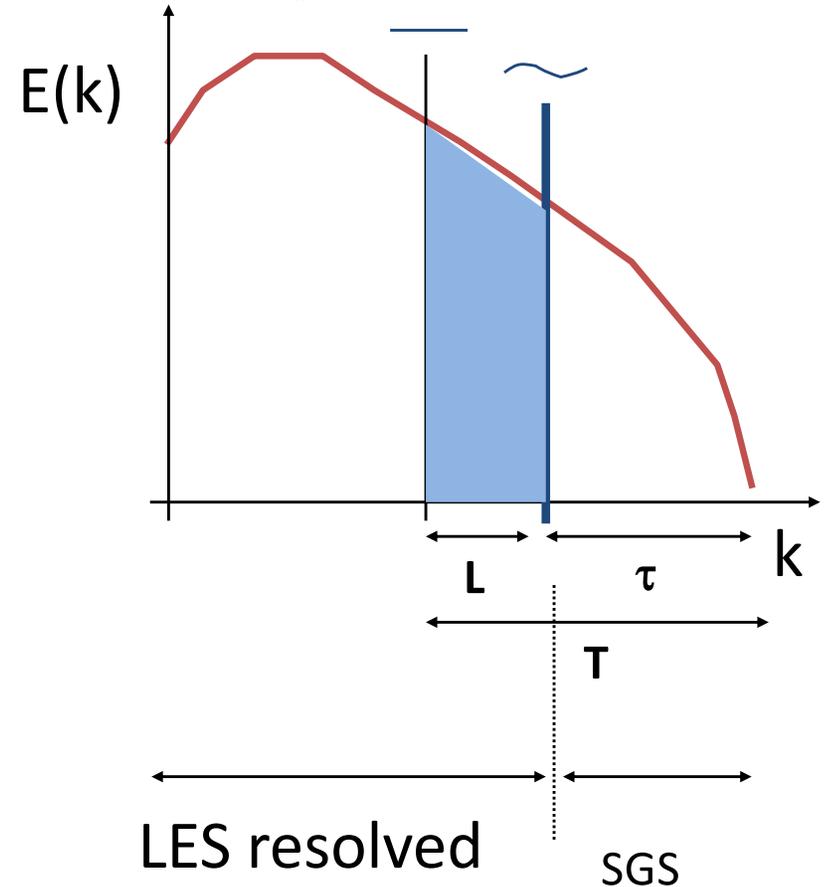
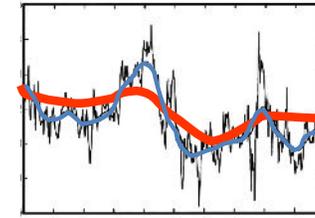
$$L_{ij} - (T_{ij} - \tau_{ij}) = 0$$

$$-2(c_s 2\Delta)^2 |\widetilde{S}| \widetilde{S}_{ij} \quad -2(c_s \Delta)^2 |\widetilde{S}| \widetilde{S}_{ij}$$

Assumes scale-invariance:

$$L_{ij} - c_s^2 M_{ij} = 0$$

where  $M_{ij} = 2\Delta^2 \left( \overline{|\widetilde{S}| \widetilde{S}_{ij}} - 4 |\widetilde{S}| \widetilde{S}_{ij} \right)$



# Germano identity and dynamic model

(Germano et al. 1991):

$$L_{ij} - c_s^2 M_{ij} = 0$$

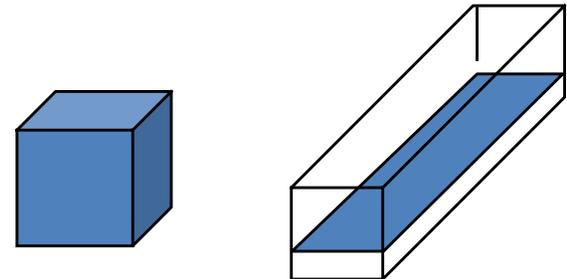
Over-determined system:  
solve in “some average sense”  
(minimize error, Lilly 1992):

$$E = \left\langle \left( L_{ij} - c_s^2 M_{ij} \right)^2 \right\rangle$$

Minimized when:

$$c_s^2 = \frac{\langle L_{ij} M_{ij} \rangle}{\langle M_{ij} M_{ij} \rangle}$$

Averaging over regions of  
statistical homogeneity  
or fluid trajectories



**“Machine Learning”:**  
Computer “learns”  $C_s$  by focusing  
on the right statistics/physics

# Lagrangian averaging

- How and from where to "learn" from large scales:
- Time averaging: should be in Lagrangian frame for Galilean invariance....
- Averaging backward in time along particle trajectory.

$$\mathcal{L}_f = \int_{-\infty}^t f(\mathbf{z}(t'), t') \frac{1}{T} \exp\left(-\frac{t-t'}{T}\right) dt'$$



According to this model, the Smagorinsky coefficient is evaluated as

$$c_s = \mathcal{J}_{LM} / \mathcal{J}_{MM}, \quad (13.268)$$

CM, Lund &  
Cabot (JFM, 1996)

where  $\mathcal{J}_{LM}$  and  $\mathcal{J}_{MM}$  represent the averages  $(M_{ij}\mathcal{L}_{ij})_{ave}$  and  $(M_{ij}M_{ij})_{ave}$ . The simple relaxation equation

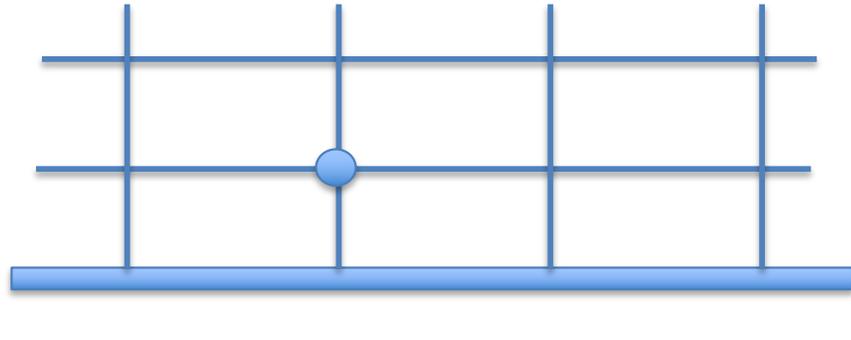
$$\frac{\overline{D}\mathcal{J}_{MM}}{\overline{D}t} = -(\mathcal{J}_{MM} - M_{ij}M_{ij})/T \quad (13.269)$$

is solved for  $\mathcal{J}_{MM}$ , where  $T$  is a specified relaxation time. This is equivalent to averaging along the particle path, with relative weight  $\exp[-(t-t')/T]$  at the earlier time  $t'$ . The similar equation that is solved for  $\mathcal{J}_{LM}$  is

$$\frac{\overline{D}\mathcal{J}_{LM}}{\overline{D}t} = -I_0(\mathcal{J}_{LM} - M_{ij}\mathcal{L}_{ij})/T, \quad (13.270)$$

# Scale dependence: highly relevant for wall-modeled LES

$$\nu_T = [C_s(\Delta) \Delta]^2 |\tilde{\mathbf{S}}|$$



$$\Delta \sim y$$

$$l \sim \kappa y$$

↓

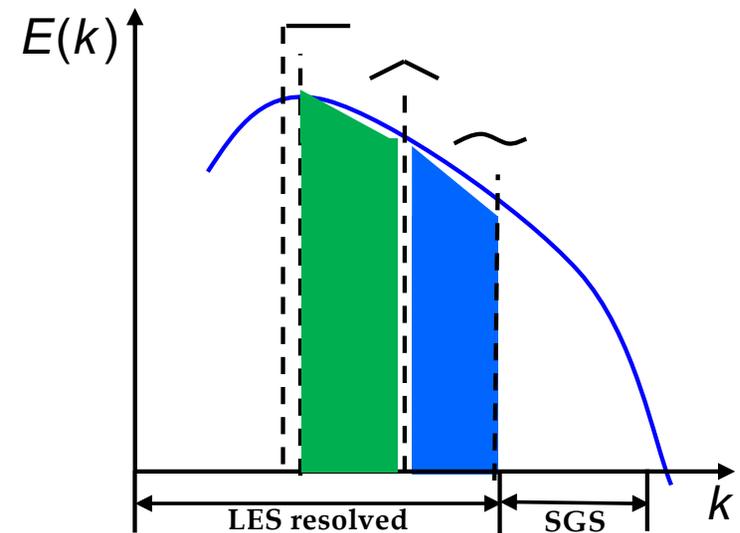
➤ Scale-dependence:

$\Delta$  and esp.  $2\Delta$  **not** in inertial range !!

$$C_s(\Delta) \sim \Delta^\varphi$$

$$c_s(\hat{\Delta}) = \gamma_c c_s(\Delta)$$

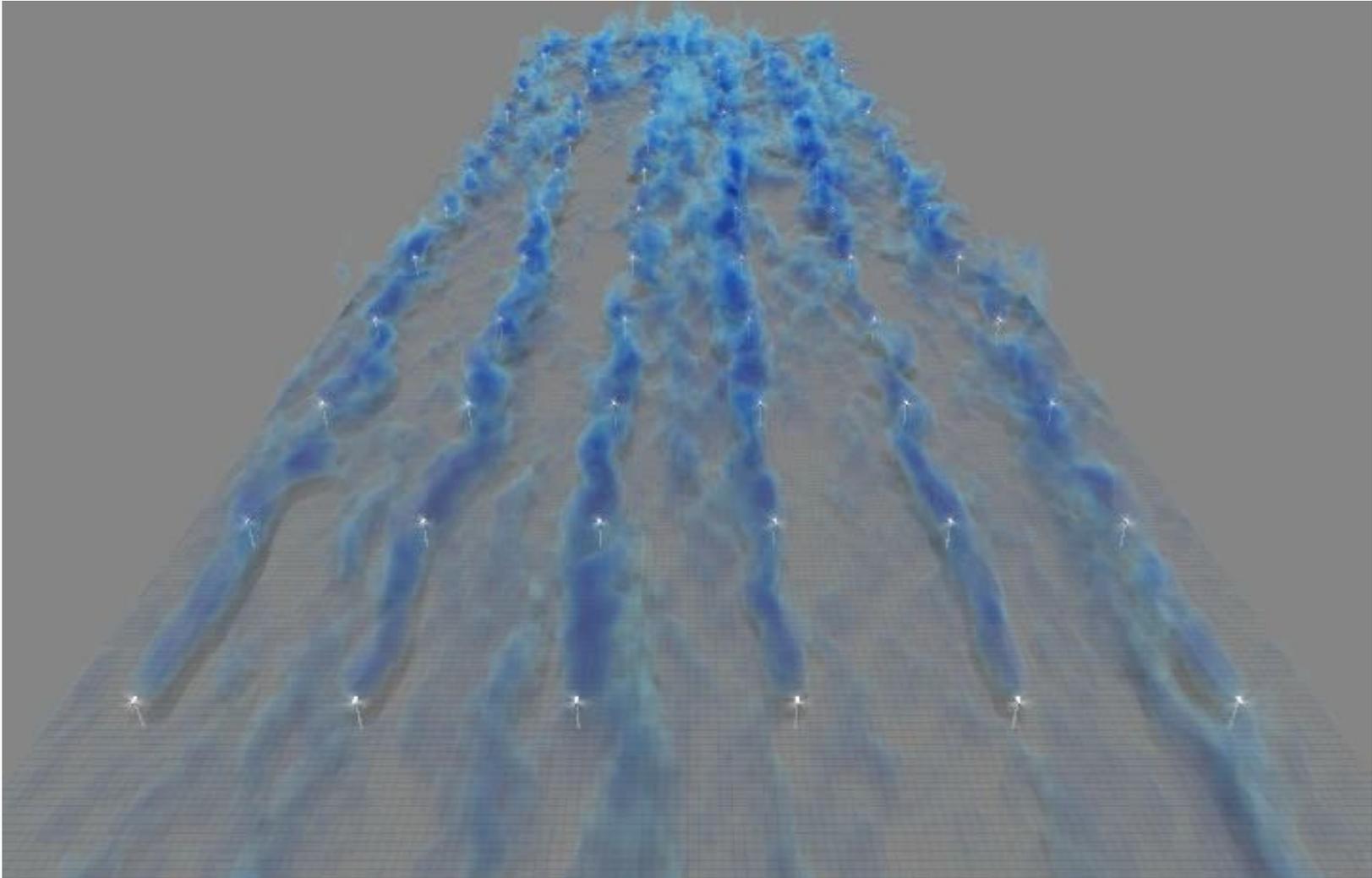
$$\gamma_c = c_{s,\hat{\Delta}}^2 / c_{s,\Delta}^2 = c_{s,\bar{\Delta}}^2 / c_{s,\hat{\Delta}}^2$$



Test-filtering at 2 scales: e.g.  $2\Delta$  and  $4\Delta$

# Example application of LES: Wind farm simulations using LASD SGS model (and ADM)

Stevens et al. (2016)



Code: LESGO

# A pertinent new “canonical turbulent flow”: The windturbine-array boundary layer (WTABL) (=WAKES + ATMOSPHERIC BOUNDARY LAYER)



Horns Rev 1: Photograph: Christian Steiness



Photo credit: Bel Air



## Collaborators:

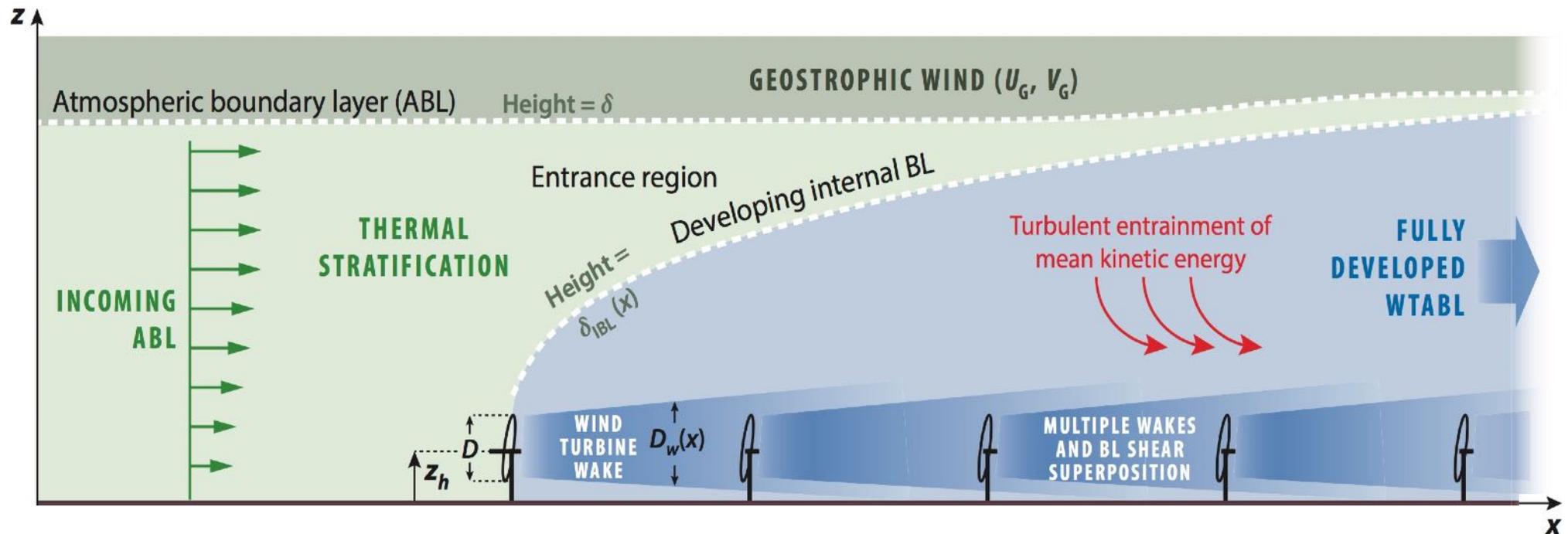
- Richard J.A.M. Stevens (now Twente U., NL) – LES + CWBL
- Marc Calaf (now U. Utah) – LES + BL models
- Prof. Johan Meyers (KU Leuven, B) – LES
- Dennice Gayme (JHU) – reduced models + control
- Juliaan Bossuyt (KU Leuven, JHU visiting student, B) – windtunnel
- Michael Howland (JHU undergrad till 2016) – windtunnel
- Michael Wilczek (now MPI Göttingen, D) – spectral theory

Funding: NSF OISE-1243882 (WINDINSPIRE project)

Simulations: XSEDE, SARA (NL) & MARCC



# Fluid mechanics of the wind turbine-array boundary layer (WTABL)



From: R.J.A.M. Stevens & C.M., "Flow structure and turbulence in wind farms", (2017), Annu. Rev. Fluid Mech. **49**, 311-339.



# Wind farm design & optimization:

great need for simple engineering (reduced) models

## 1. Mean Power optimization: mean velocity

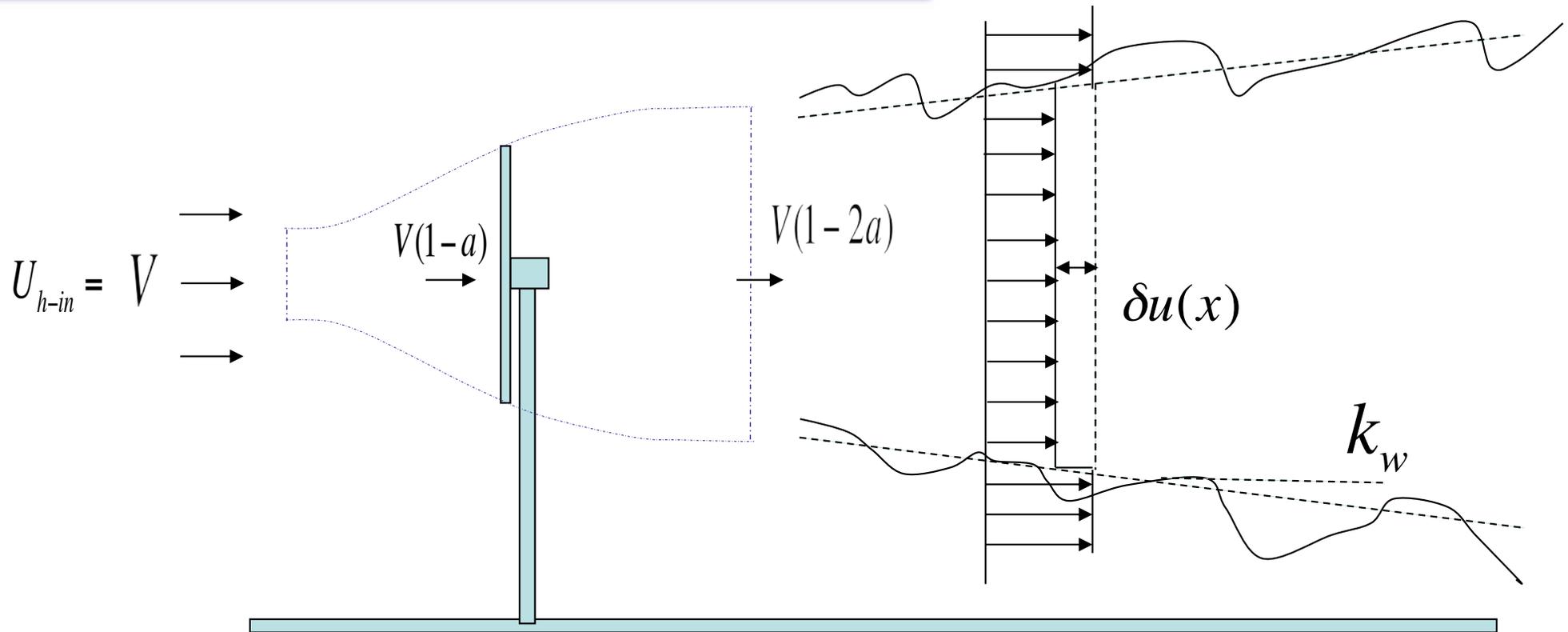
$$P_{\text{turb}} = \frac{1}{2} C_P \rho \frac{\pi}{4} D^2 U_{\text{turb}}^3$$
$$\frac{1}{P_{\text{max}}} P_{\text{tot}}(s, D, z_h, C_T, \text{layout..}) = \sum_{\text{all turbines}} \left( \frac{U_{\text{turb}}}{U_{h-in}} \right)^3$$

## 2. Fluctuations: power variability due to turbulence



# Jensen model: The single wake

Lissaman (1979) / static Jensen (1984)



inviscid momentum theory  
gives "IC" for wake model

wake model: turbulence  
governs growth rate  $k_w$  of wake

$$a = \frac{1}{2} \left( 1 - \sqrt{1 - C_T} \right)$$

$$\delta u(x, j) = U_{h0} - u(x) = \frac{2aU_{h0}}{\left( 1 + 2k_w \frac{x - x_j}{D} \right)^2}$$

# Jensen model: The wake superposition

Lissaman (1979) / Katic et al. (1986)



$$u'^2 \sim \delta u^2 \Rightarrow \Sigma u'^2 \sim \Sigma \delta u^2 \Rightarrow$$

$$\Rightarrow \delta u_{net}^2 = \Sigma \delta u_j^2 \Rightarrow 1 - \frac{U_h}{U_{h0}} = \left( \Sigma \left( \frac{\delta u_j}{U_{h0}} \right)^2 \right)^{1/2}$$

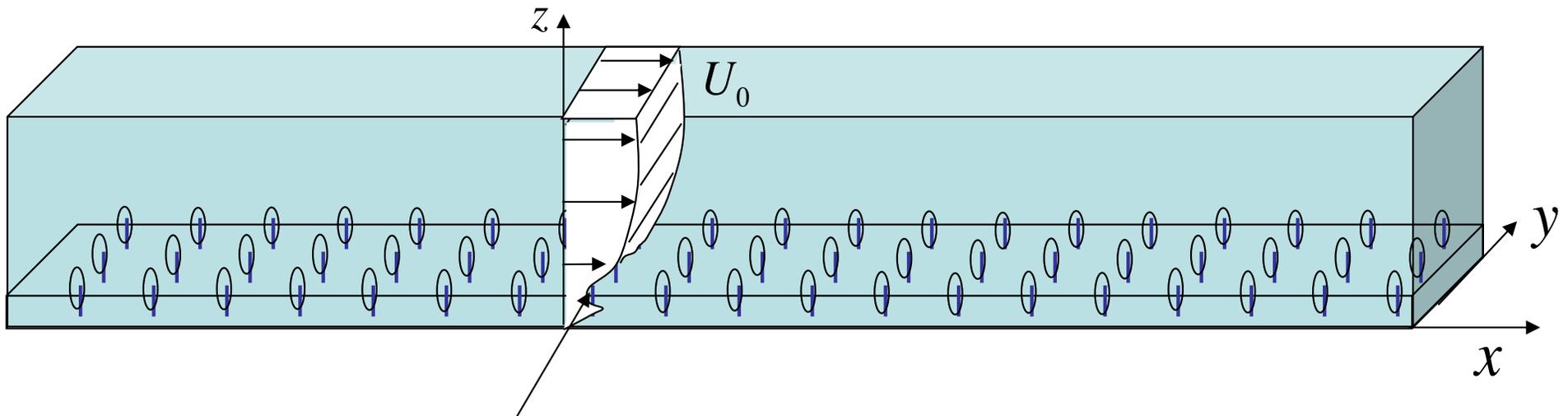
**Superposition** of squared velocity deficits, can be rationalized by assuming that kinetic energy is additive (independent turbulence fluctuations)

$$\frac{U_h(s, C_T, \dots)}{U_{h0}} = 1 - \left( 1 - \sqrt{1 - C_T} \right) \left( \sum_{j \in J_{Tk}} \left[ 1 + 2k_w \frac{x_{Tk} - x_j}{D} \right]^{-4} \right)^{1/2}$$

**But no connection to ABL structure  
(OK for small farms)**

# A boundary layer (canopy flow) view: the mean velocity vertical profiles in fully developed WTABL

---



$$U(z) = \langle \bar{u}(x, y, z) \rangle_{xy}$$

horizontal (canopy) average

# Data: from LES of WTABL typical simulation setup:

- LES code: horizontal pseudo-spectral (periodic B.C.), vertical: centered 2nd order FD (Moeng 1984, Albertson & Parlange 1999, Porté-Agel et al. 2000, Bou-Zeid et al. 2005)

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

$$\frac{\partial \tilde{\mathbf{u}}}{\partial t} + \tilde{\mathbf{u}} \cdot \nabla \tilde{\mathbf{u}} = -\nabla \tilde{p}^* - \nabla \cdot \boldsymbol{\tau} + \mathbf{f}$$

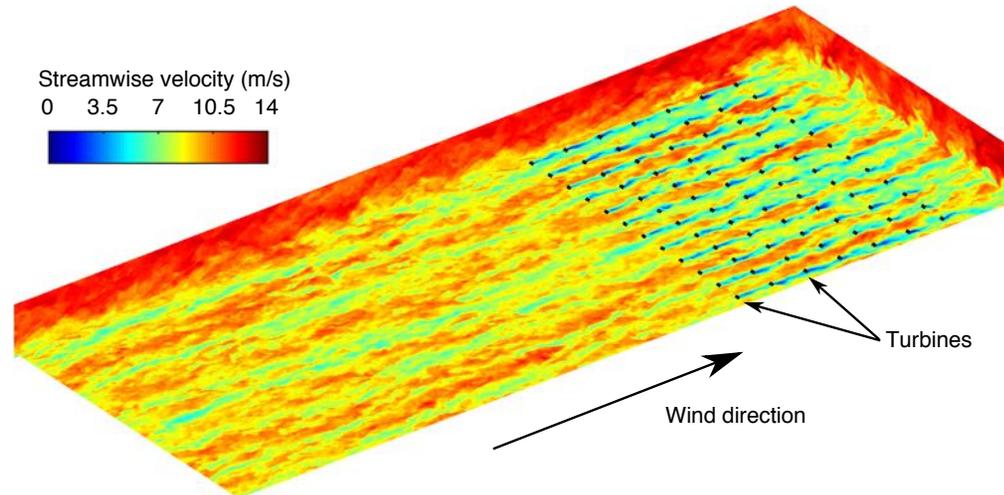
High-fidelity, but has large computational cost

Actuator disk forcing:

$$F = -\frac{1}{2} \rho A C'_T \langle u \rangle_d^2$$

Power:

$$P = \frac{1}{2} \rho A C'_T \langle u \rangle_d^3$$



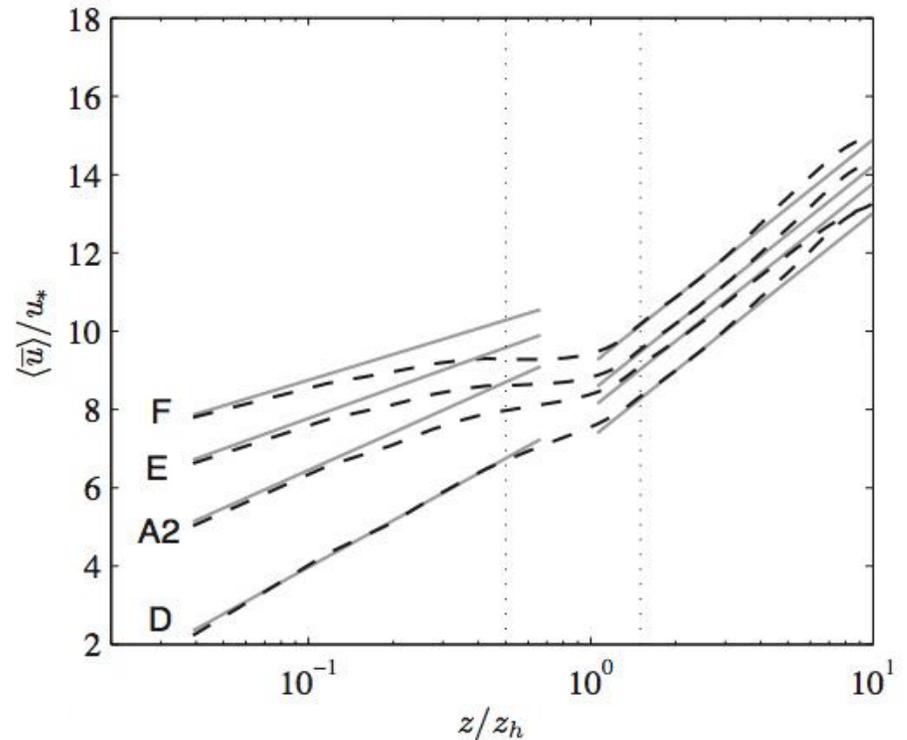
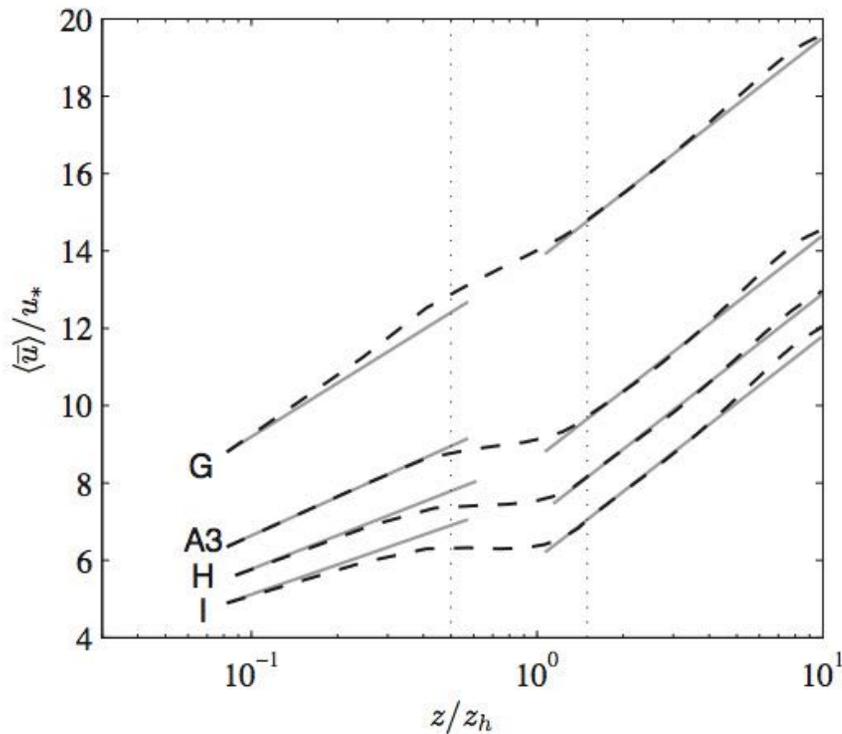
$$H = 1000 - 1500m, \quad L_x = \pi H - 2\pi H, \quad L_y = \pi H$$

$$(N_x \times N_y \times N_z) = 128 \times 128 \times 128 \rightarrow 1024 \times 512 \times 512$$

- Horizontal periodic boundary conditions (for FD-WTABL, or precursor for developing)
- Top surface: zero stress, zero w
- Bottom surface B.C.:  $w=0$  + Wall stress: Standard wall function relating wall stress to  $u(z_1)$
- Scale-dependent dynamic Lagrangian model eddy-viscosity (*no* adjustable parameters)
- More details: Calaf et al. Phys. Fluids. **22** (2010) 015110

## Horizontal mean velocity in WTABL from LES (ADM):

Calaf et al 2010 (confirming hypothesis by Frandsen 1992): 2 log-laws

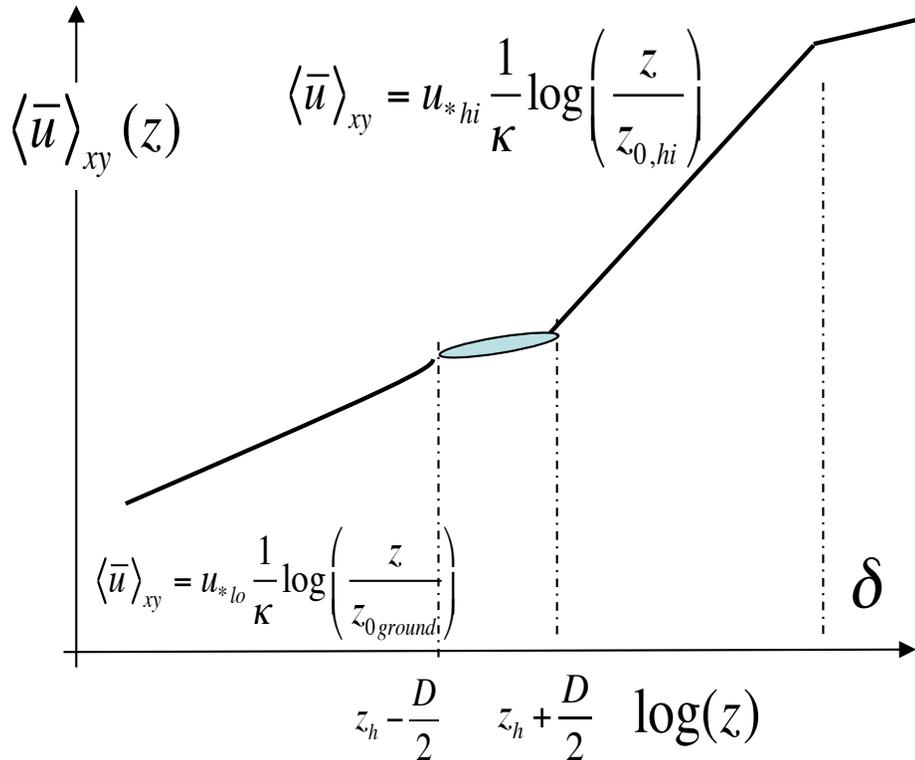


Other studies of WTABL velocity distributions:

- Cal et al. (JRSE 2010)
- Johnstone & Coleman (J Wind Eng & Ind A, 2012)
- Yang, Kang & Sotiropoulos (PoF 2012)
- Chamorro & Porté-Agel (2013)
- Chatterjee & Peet (Pys Rev Fluids 2018)
- Ghate & Lele (J Fluid Mech, 2017)

## Top down model:

S. Frandsen 1992, Frandsen et al. 2006, Calaf et al 2010, Stevens 2015..:



Two “constant stress” layers with:

$$u_{*hi}^2 \approx u_{*lo}^2 + \frac{1}{2} C_T \frac{\pi}{4s_x s_y} U_h^2$$

In wake layer, reduced slope:

$$\frac{\partial \langle \bar{u} \rangle}{\partial z} = \frac{1}{\kappa u_* z_h + v_w} u_*^2$$

Effective wind farm roughness:

$$z_{0,hi} = z_h \left(1 + \frac{D}{2z_h}\right)^\beta \exp\left[-\left[\frac{\pi C_T}{8\kappa^2 s_x s_y} + \left(\ln\left[\frac{z_h}{z_{0,ground}} \left(1 - \frac{D}{2z_h}\right)^\beta\right]\right)^{-2}\right]^{-1/2}\right]$$

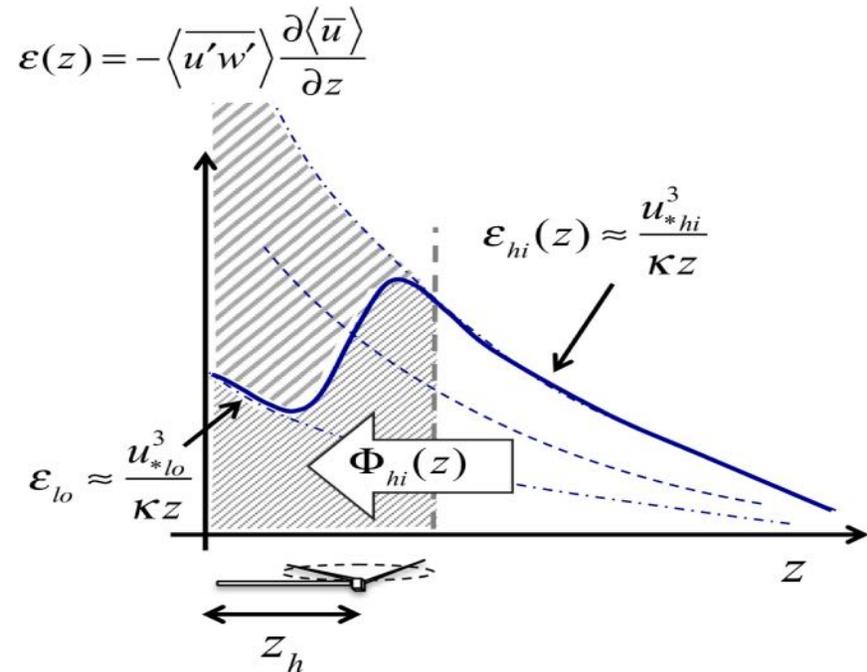
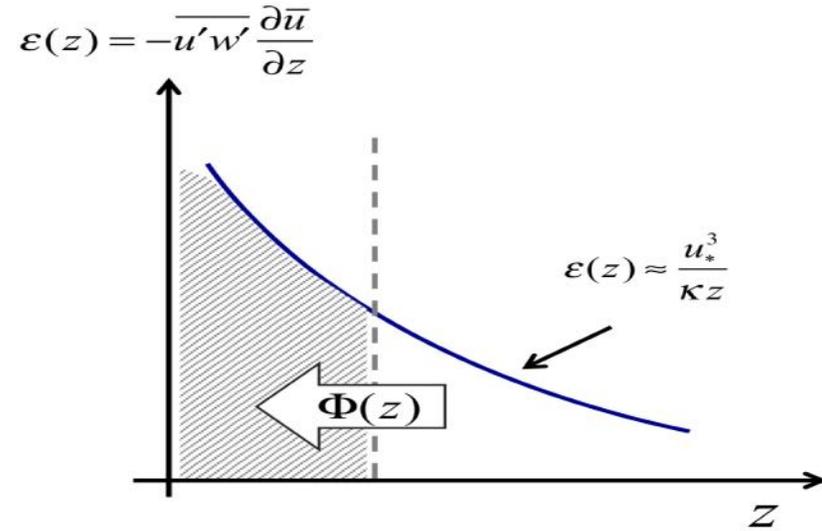
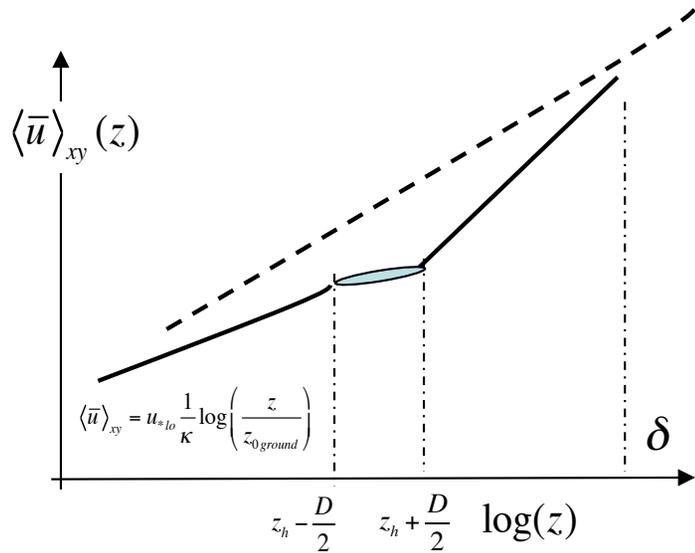
**Mean velocity at hub height,  
normalized by ABL unperturbed  
inflow :**

$$\frac{U_h(s, C_T, \dots)}{U_{h0}} = \frac{\ln(\delta / z_{0,lo})}{\ln(\delta / z_{0,hi})} \ln\left[\left(\frac{z_h}{z_{0,hi}}\right) \left(1 + \frac{D}{2z_h}\right)^\beta\right] \left[\ln\left(\frac{z_h}{z_{0,lo}}\right)\right]^{-1}$$

# Top down model:

**SIDE NOTE:** Top-down model enables us to understand fate of mean kinetic energy in the WTABL:

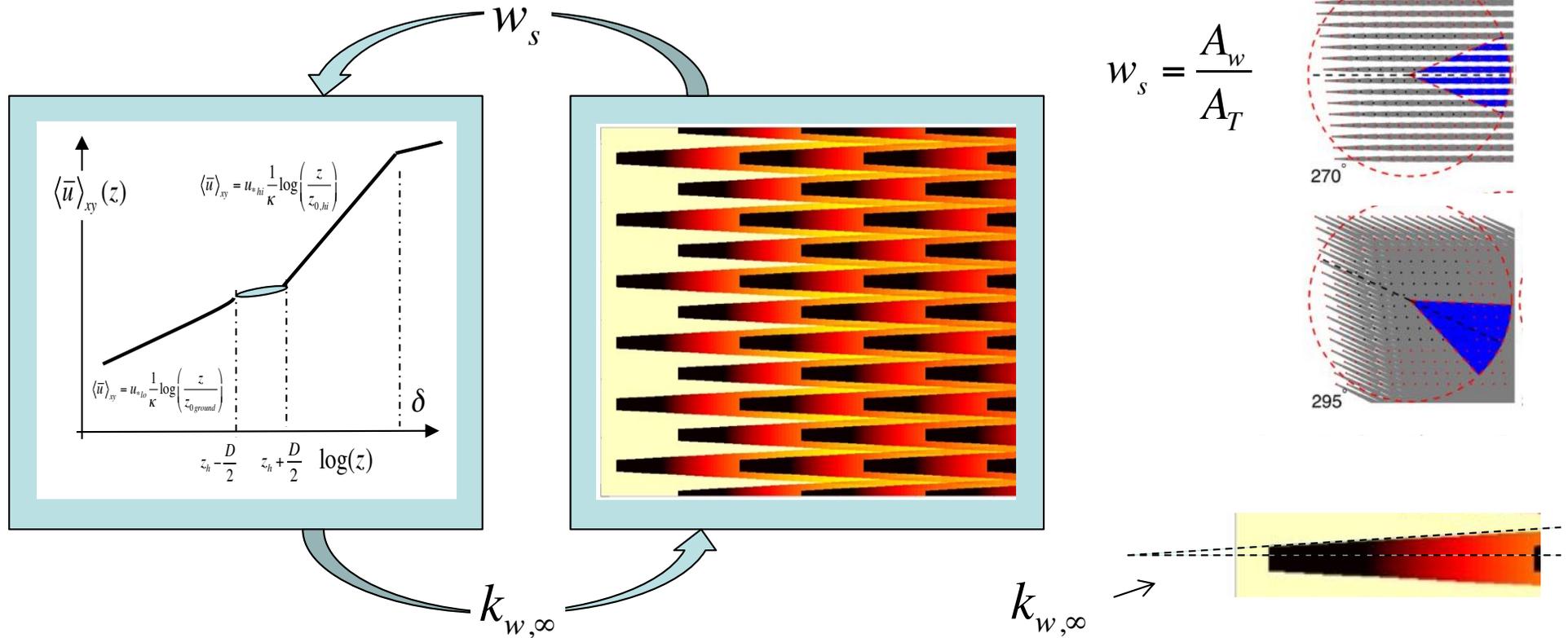
$$\frac{1}{2} \langle \bar{u} \rangle_{xy}^2$$



Instead of being dissipated entirely in BL, mean KE extracted by turbines and dissipated

# Coupled wake boundary layer model (CWBL)

Stevens, Gayme & CM, Wind Energy 19, 2023-2040 (2016)

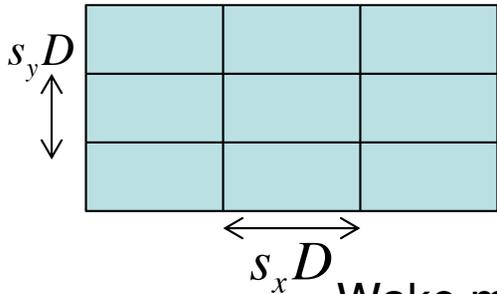


$$\frac{\ln(\delta / z_{0,lo})}{\ln(\delta / z_{0,hi})} \ln \left[ \left( \frac{z_h}{z_{0,hi}} \right) \left( 1 + \frac{D}{2z_h} \right)^\beta \right] \left[ \ln \left( \frac{z_h}{z_{0,lo}} \right) \right]^{-1} = \frac{1}{N_d} \sum_{k=1}^{N_d} \left[ 1 - 2a \left( \sum_{j \in J_{A,k}} \left[ 1 + k_{w,\infty} \frac{x_{T,k} - x_j}{R} \right]^{-4} \right)^{1/2} \right]$$

$$z_{0,hi} = z_h \left( 1 + \frac{D}{2z_h} \right)^\beta \exp \left( - \left[ \frac{\pi C_T}{8 \kappa^2 w_s s_x s_y} + \left( \ln \left[ \frac{z_h}{z_{0,ground}} \left( 1 - \frac{D}{2z_h} \right)^\beta \right] \right)^{-2} \right]^{-1/2} \right)$$

# Model comparisons with LES (fully developed)

**CWBL model:** distinguishes well between aligned & staggered cases



$$\left(\frac{U_h(\infty)}{U_{h-0}}\right)^3$$

$$s = \sqrt{s_x s_y}$$

Color indicates spanwise spacing

$s_y=3.49$

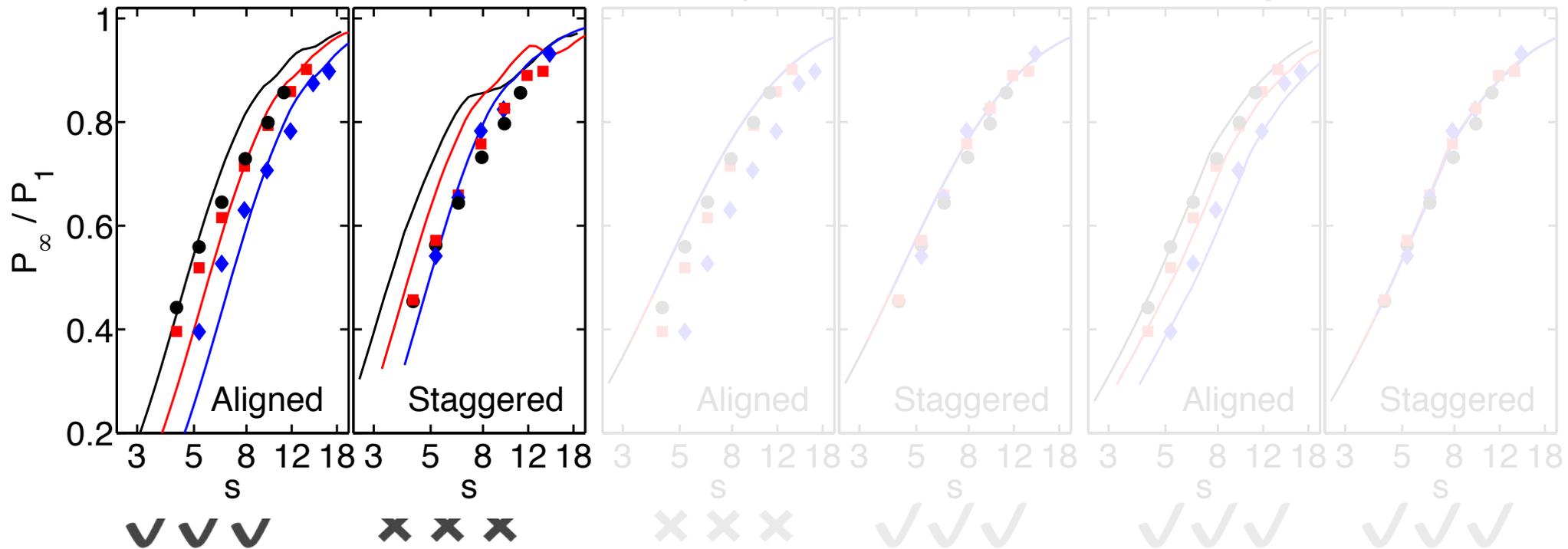
$s_y=5.23$

$s_y=7.85$

Wake model

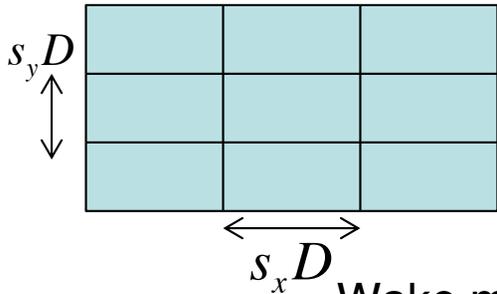
Top-down model

Coupled wake boundary layer model



# Model comparisons with LES (fully developed)

**CWBL model:** distinguishes well between aligned & staggered cases



$$\left(\frac{U_h(\infty)}{U_{h-0}}\right)^3 \quad s = \sqrt{s_x s_y}$$

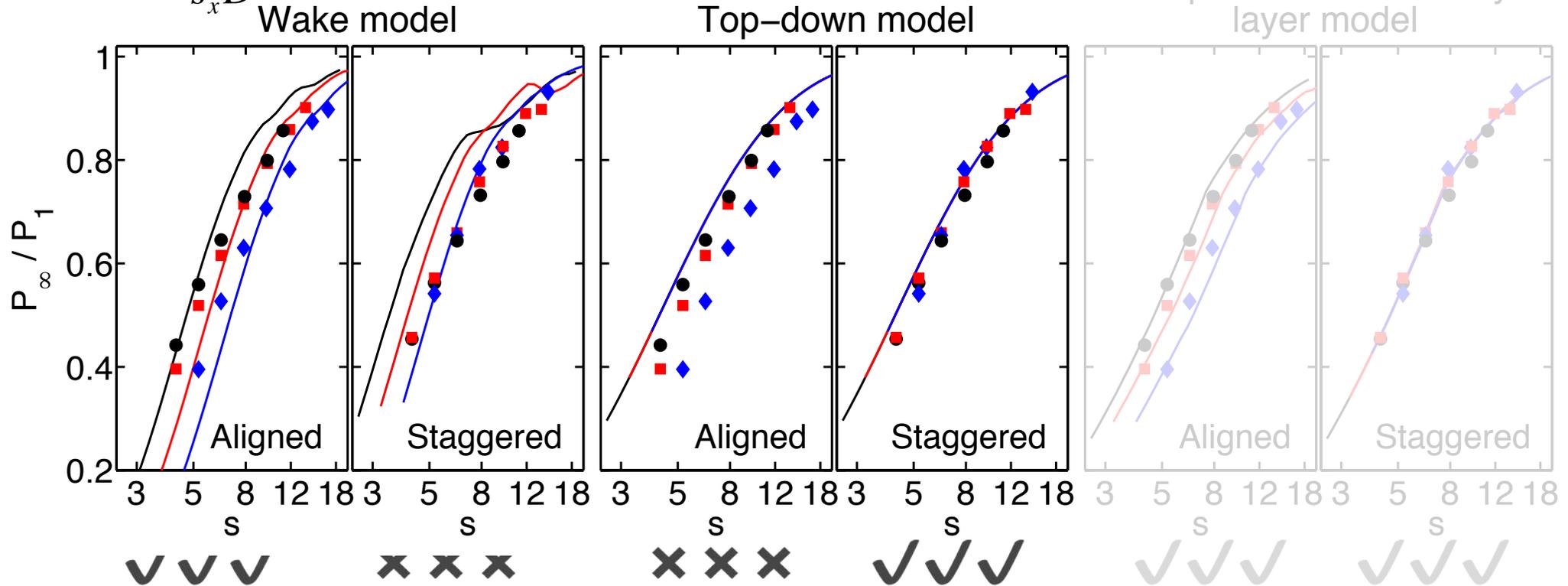
Color indicates spanwise spacing

$s_y=3.49$

$s_y=5.23$

$s_y=7.85$

Coupled wake boundary layer model

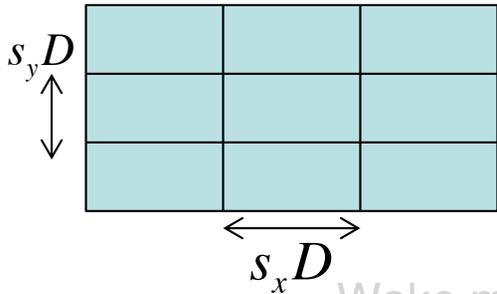


O : LES

-----: CWBL

# Model comparisons with LES (fully developed)

**CWBL model:** distinguishes well between aligned & staggered cases



$$\left(\frac{U_h(\infty)}{U_{h-0}}\right)^3 \quad s = \sqrt{s_x s_y}$$

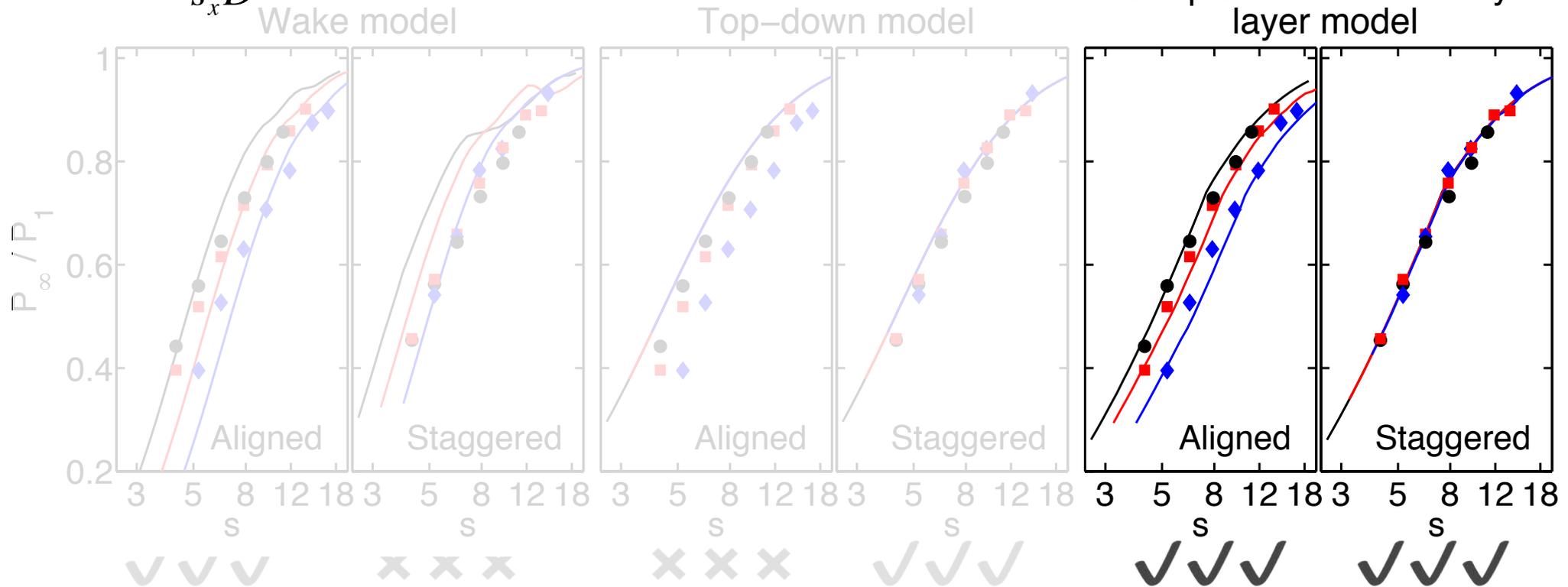
Color indicates spanwise spacing

$s_y=3.49$

$s_y=5.23$

$s_y=7.85$

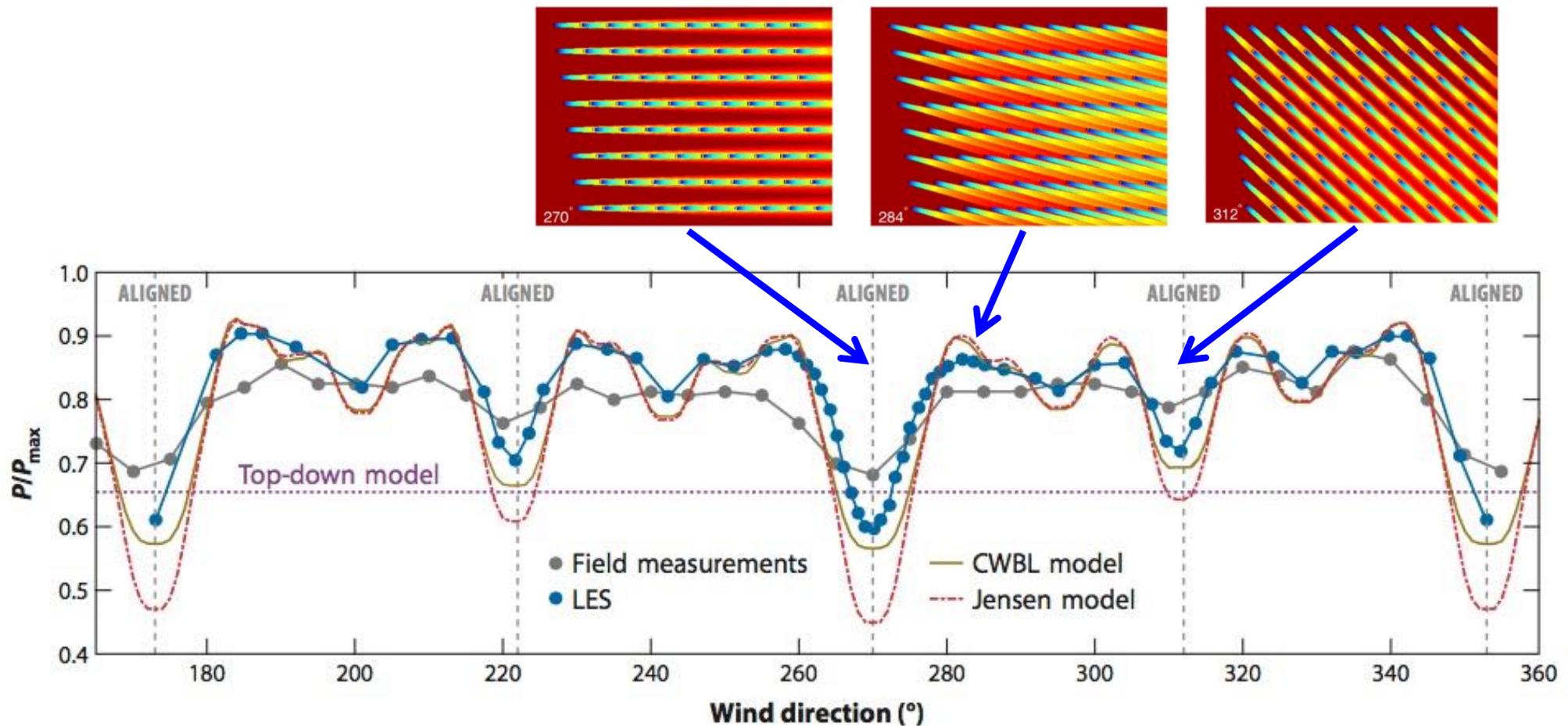
Coupled wake boundary layer model



O : LES

-----: CWBL

# Model comparisons with LES and field data (Horns Rev)

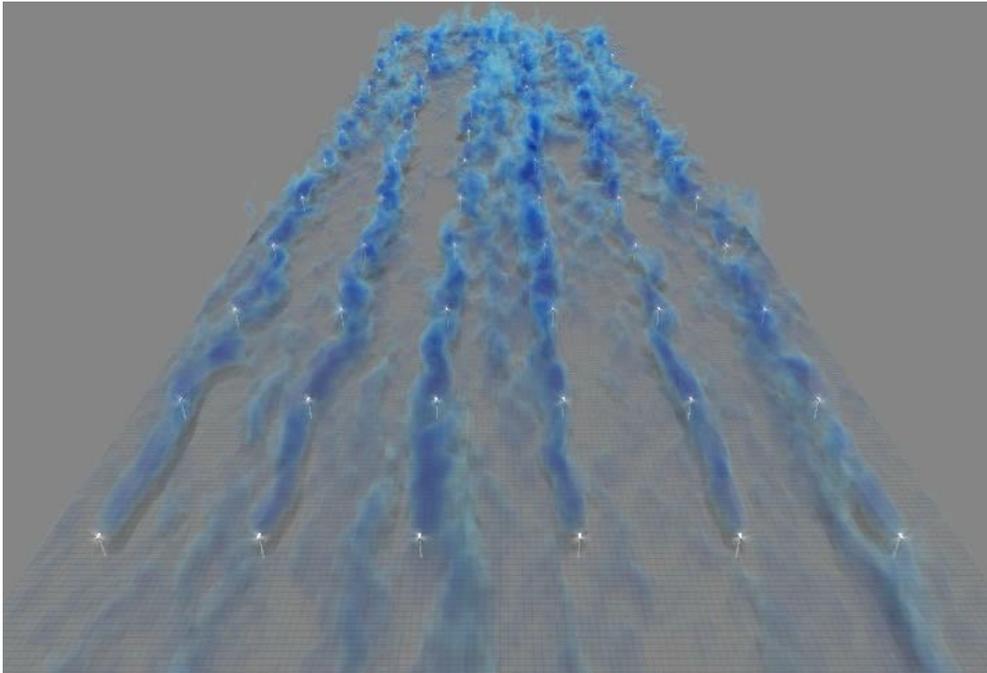


**Figure 8**

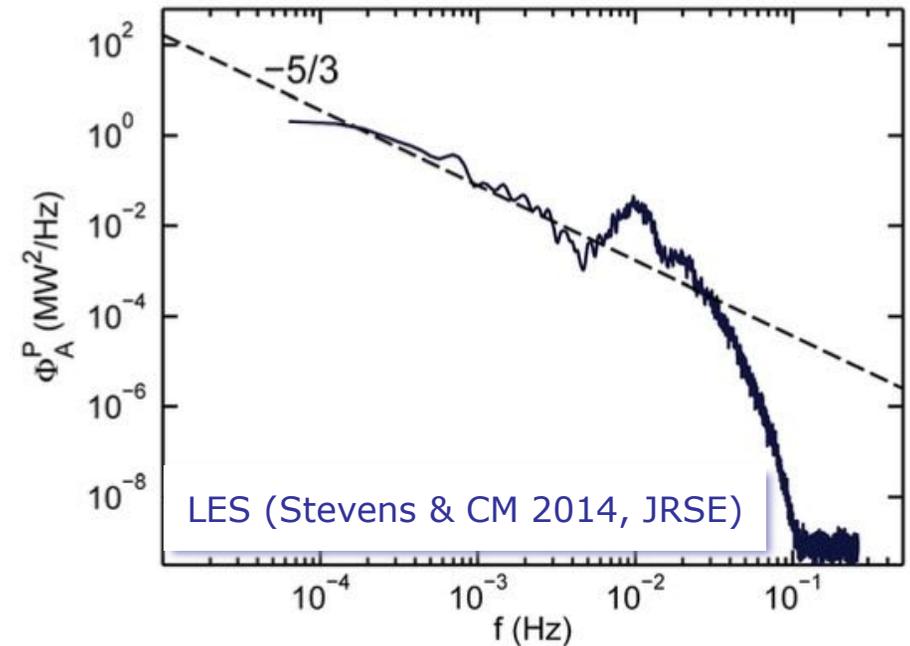
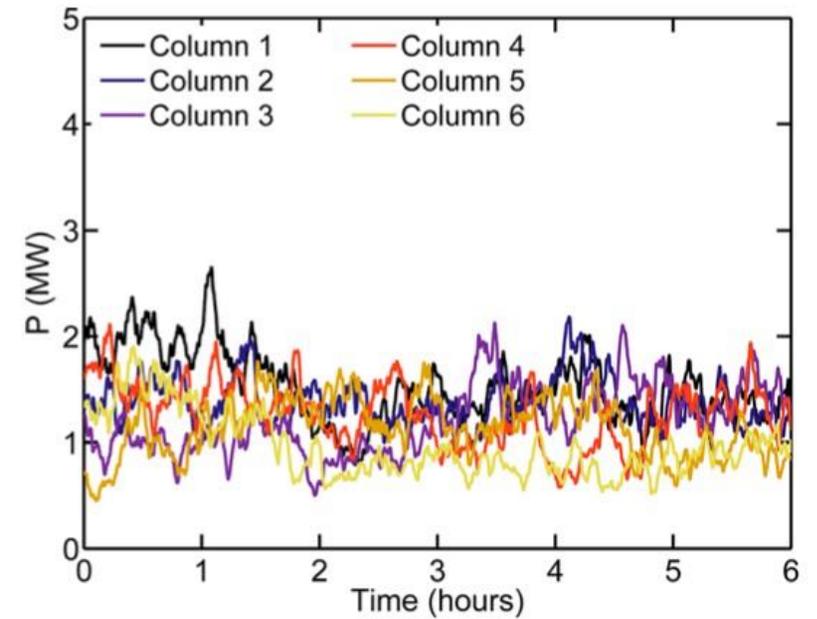
Normalized total power output  $P/P_{\max}$  of Horns Rev wind farm as a function of the incoming wind direction, where  $P_{\max}$  is the power of a non-wake-affected turbine times the number of turbines. The field measurement data are digitally extracted from the figure on page 25 of Peña et al. (2013). The large-eddy simulation (LES) results are from Porté-Agel et al. (2013); the coupled wake boundary layer (CWBL), Jensen, and top-down results are from Stevens et al. (2016b). Figure adapted with permission from Stevens et al. (2016b, figure 8).

# Temporal fluctuations in power:

Simulations: R.J.A.M. Stevens et al,  
JRSE 6, 023105 (2014), using ADM  
in JHU-LES code

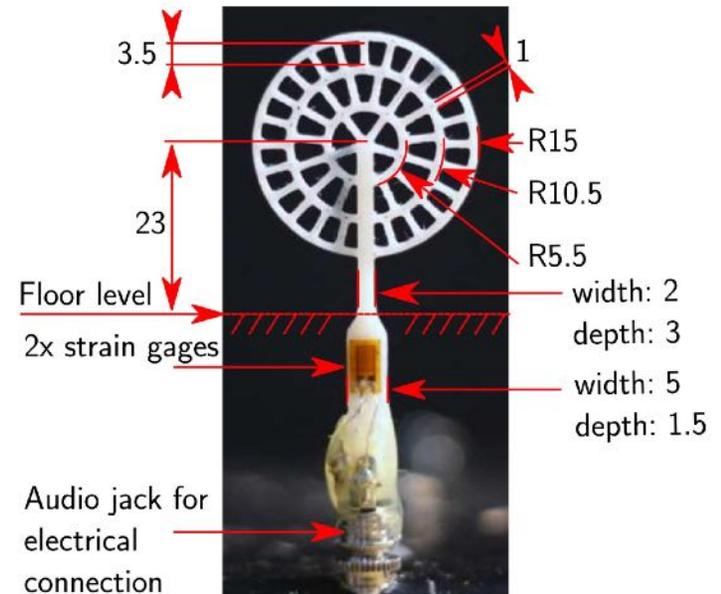
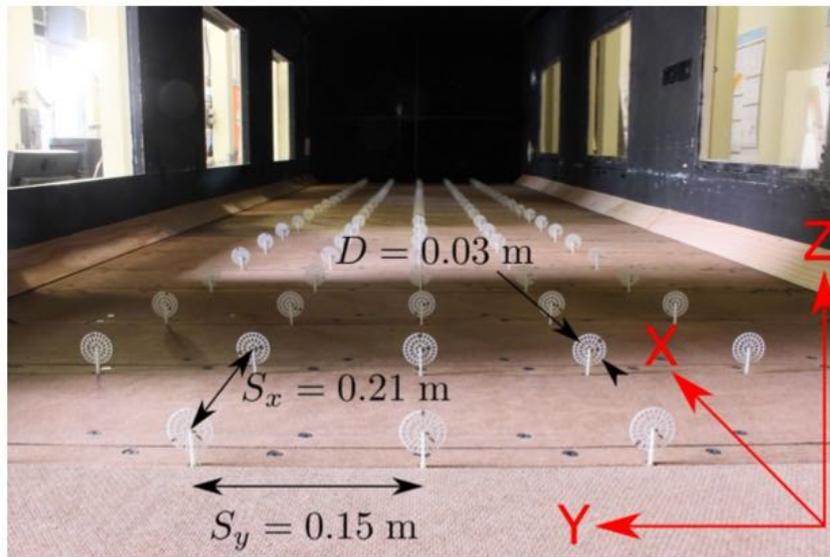
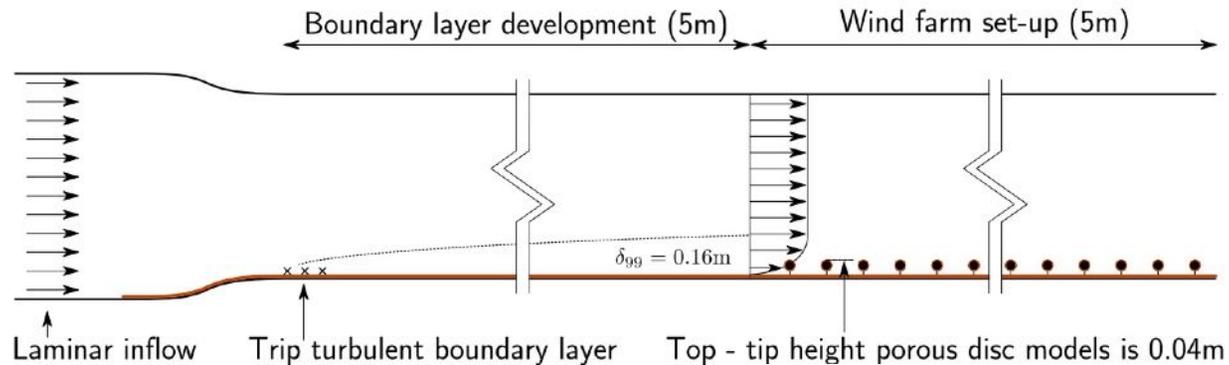


Visualization courtesy of D. Brock  
(Extended Services XSEDE)



# Wind tunnel tests in a “micro-windfarm” in the Corrsin wind tunnel: (Juliaan Bossuyt’s thesis, KU Leuven)

J. Bossuyt, CM & J. Meyers (Exp Fluids 2016, JFM 2017)



# Flyby over micro-windfarm in Corrsin wind tunnel at JHU (staggered)

100 wind turbines: 20 rows – 5 columns  
7D streamwise spacing – 5D spanwise spacing

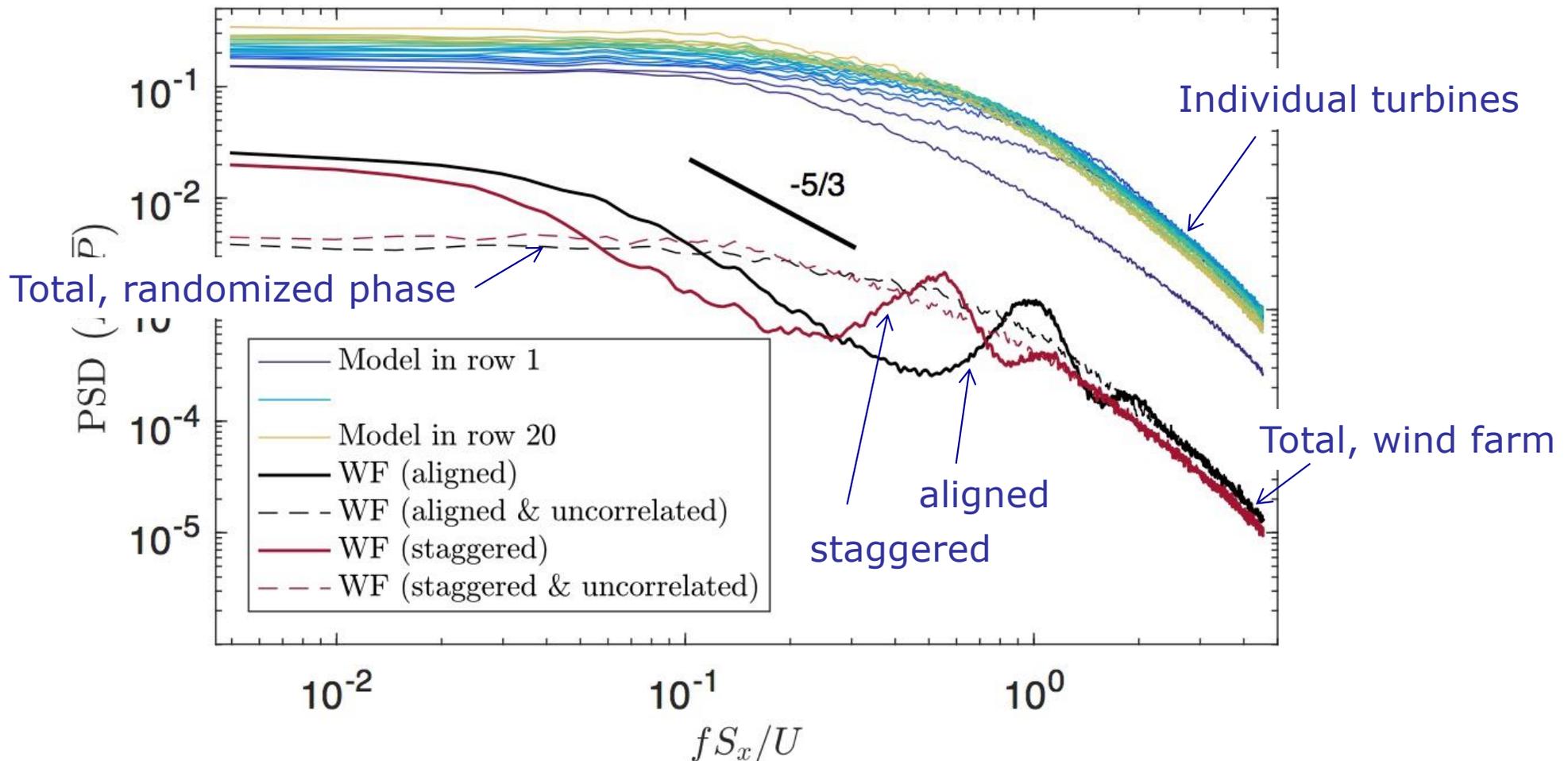


# Power-spectral density of “power” fluctuations:

$$F_i(t) = \frac{1}{2} \rho C_T A \langle u(t) \rangle_i^2$$

$$P_i(t) = \frac{1}{2} \rho C_P A \langle u(t) \rangle_i^3 \approx \frac{C_P}{C_T} \left( \frac{1}{2} \rho A \right)^{-1/2} F(t)_i^{3/2}$$

(~ valid in region II)



Bossuyt et al. JFM (2017)

## Temporal fluctuations in power:

$$P_{tot}(t; s, D, z_h, C_T, layout..) = \sum \frac{1}{2} c_p \rho A (U_h(t))^3$$

- Spectral properties of fluctuations delivered to grid

$$E_P(\omega; s, D, z_h, C_T, layout..) = PSD(P')$$

**We seek analytical models of spectral properties as function of wind farm design parameters (spacing, etc..)**

# Interpret power as discrete sampling of TBL:

$$P_i(t) = \bar{P}_i + P_i'(t) \approx U^3 + 3U^2 u'(t) + h.o.t.$$

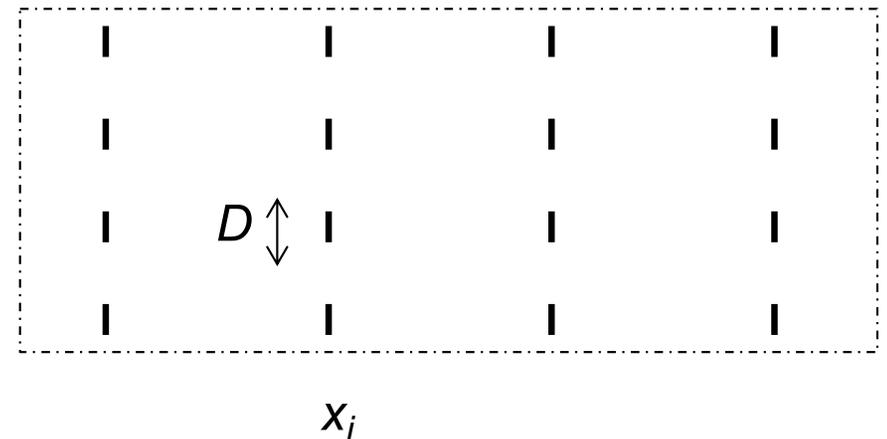
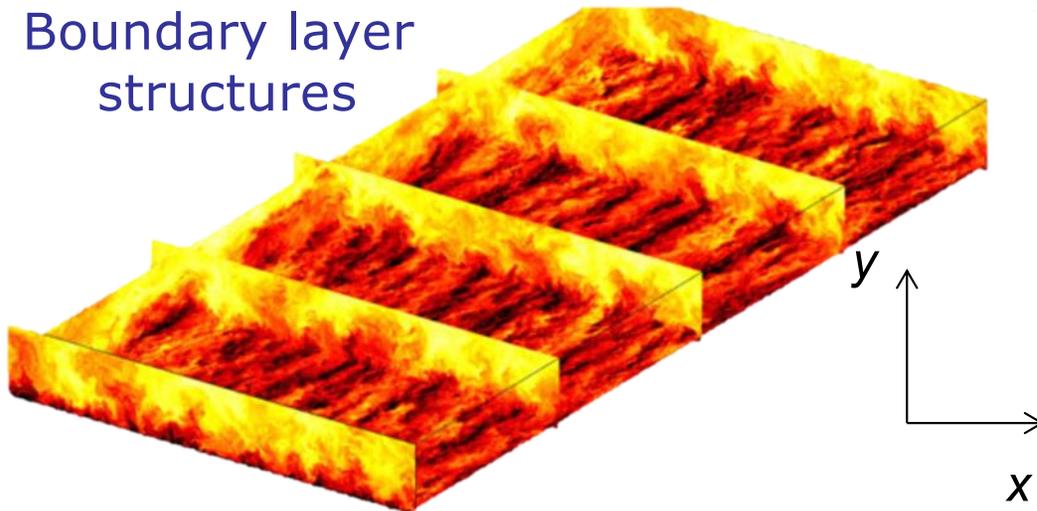
(linearization, but see Bandi (PRL 2017))

$$P'_{WF} = \sum P_i' \approx C_2 \sum \langle u \rangle_i'$$

“Transfer function”:

$$g(x, y) = \sum_{i=1}^N \delta(x - x_i) \frac{1}{D} H\left(\frac{D}{2} - |y - y_i|\right).$$

Boundary layer structures



$$E_{P'}(\omega) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \underbrace{|\hat{g}(k_1, k_2)|^2}_{\text{Transfer function}} \underbrace{E_{11}(k_1, k_2, \omega, z_h)}_{\text{Input}} dk_1 dk_2$$

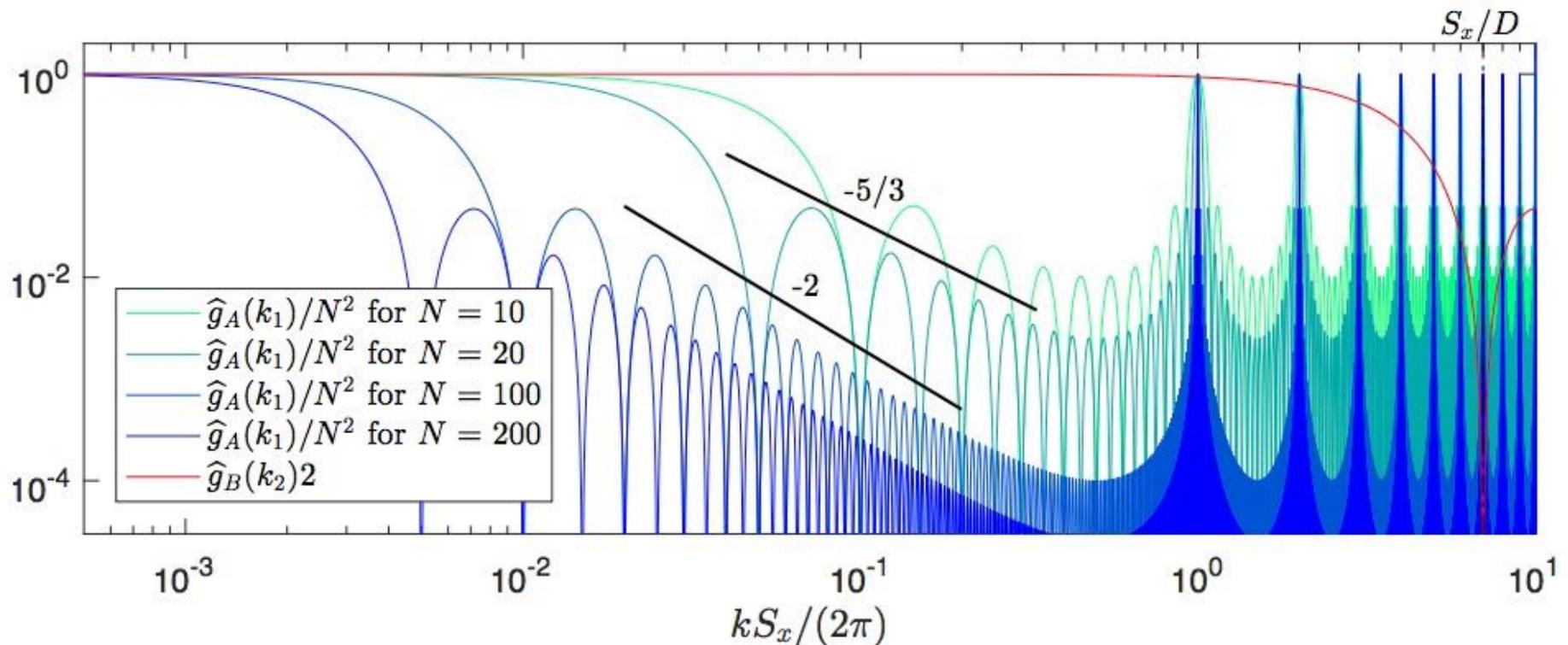
Needed:



# Transfer function of turbine array (spacing, layout)

$$g(x, y) = \sum_{i=1}^N \delta(x - x_i) \frac{1}{D} H \left( \frac{D}{2} - |y - y_i| \right).$$

$$|\hat{g}(k_1, k_2)|^2 = \left( \frac{\sin(k_2 \frac{D}{2})}{k_2 \frac{D}{2}} \right)^2 \left( \sum_{i=1}^N \sum_{j=1}^N \cos(k_1(x_i - x_j) + k_2(y_i - y_j)) \right).$$



# Analytical model for wave#-freq spectrum of BL turbulence $E_{11}(k_x, k_y, \omega; z_h)$ :

$$E_{11}(k_x, k_y, \omega; z) = \left\{ \left[ 1 - \theta_\alpha \right] A \left[ \left( \frac{1}{H} \right)^4 + k_x^4 \right]^{-1/4} + \theta_\alpha \frac{\Gamma\left(\frac{1}{3}\right)}{5\sqrt{\pi}\Gamma\left(\frac{5}{6}\right)} C_K \varepsilon^{2/3} \left[ 1 - \frac{8}{11} \frac{k_x^2}{k^2} \right] k^{-8/3} \right\} \left[ 2\pi\sigma^2(z) \right]^{-1/2} \exp\left[ -\frac{(\omega - \mathbf{k} \cdot \mathbf{U})^2}{2\sigma^2(z)} \right]$$

$$U(z) = \frac{u_*}{\kappa} \log\left(\frac{z}{z_0}\right)$$

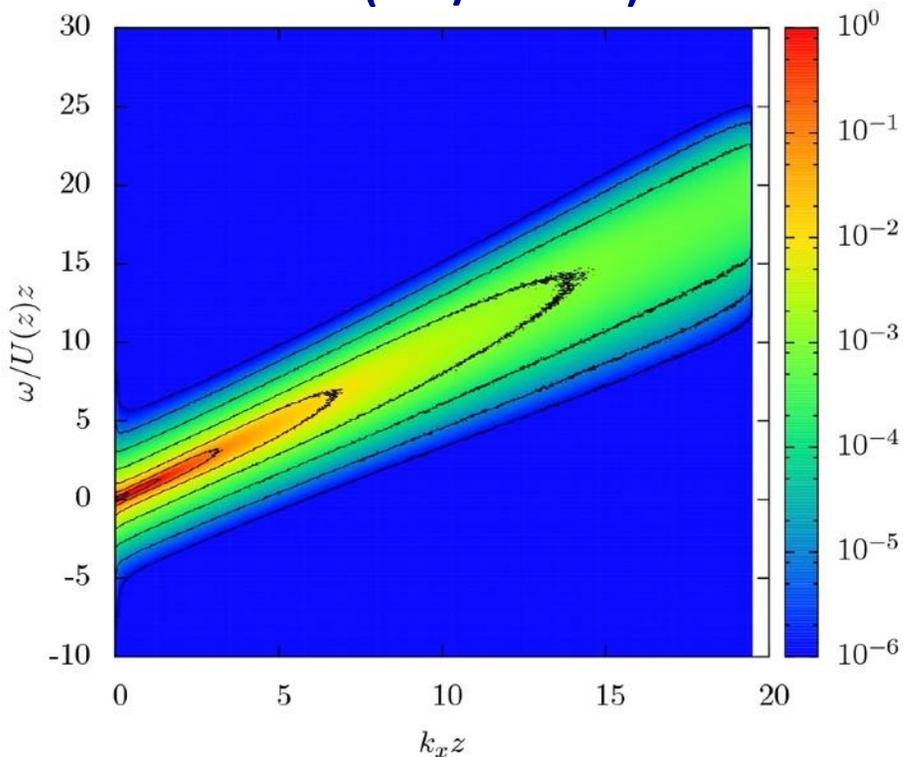
$$\langle v_x^2 \rangle = u_*^2 \left[ B - A \log\left(\frac{z}{H}\right) \right]$$

Wilczek et al. JFM 2015

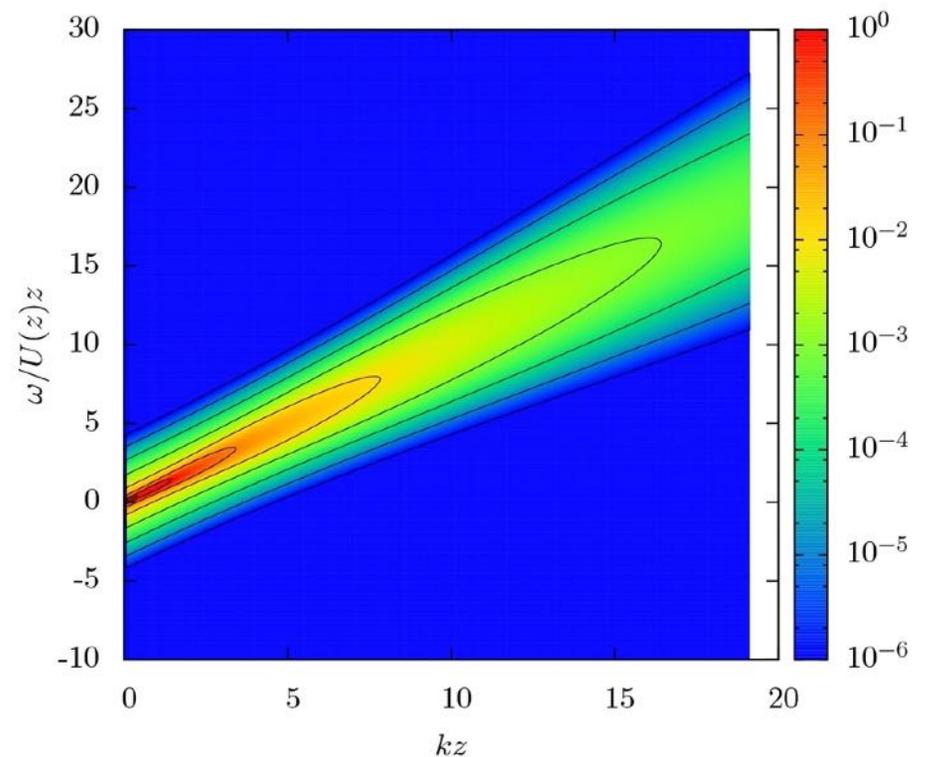
$$\sigma^2(z) = \langle (\mathbf{v} \cdot \mathbf{k})^2 \rangle = \langle v_x^2 \rangle k_x^2 + \langle v_y^2 \rangle k_y^2$$

$$\sigma^2(z) = \langle v_x^2 \rangle [k_x^2 + Ck_y^2], \quad A=0.96, \quad B=2.41, \quad C=0.33, \quad \kappa=0.4$$

LES data (at  $z/H=0.15$ )



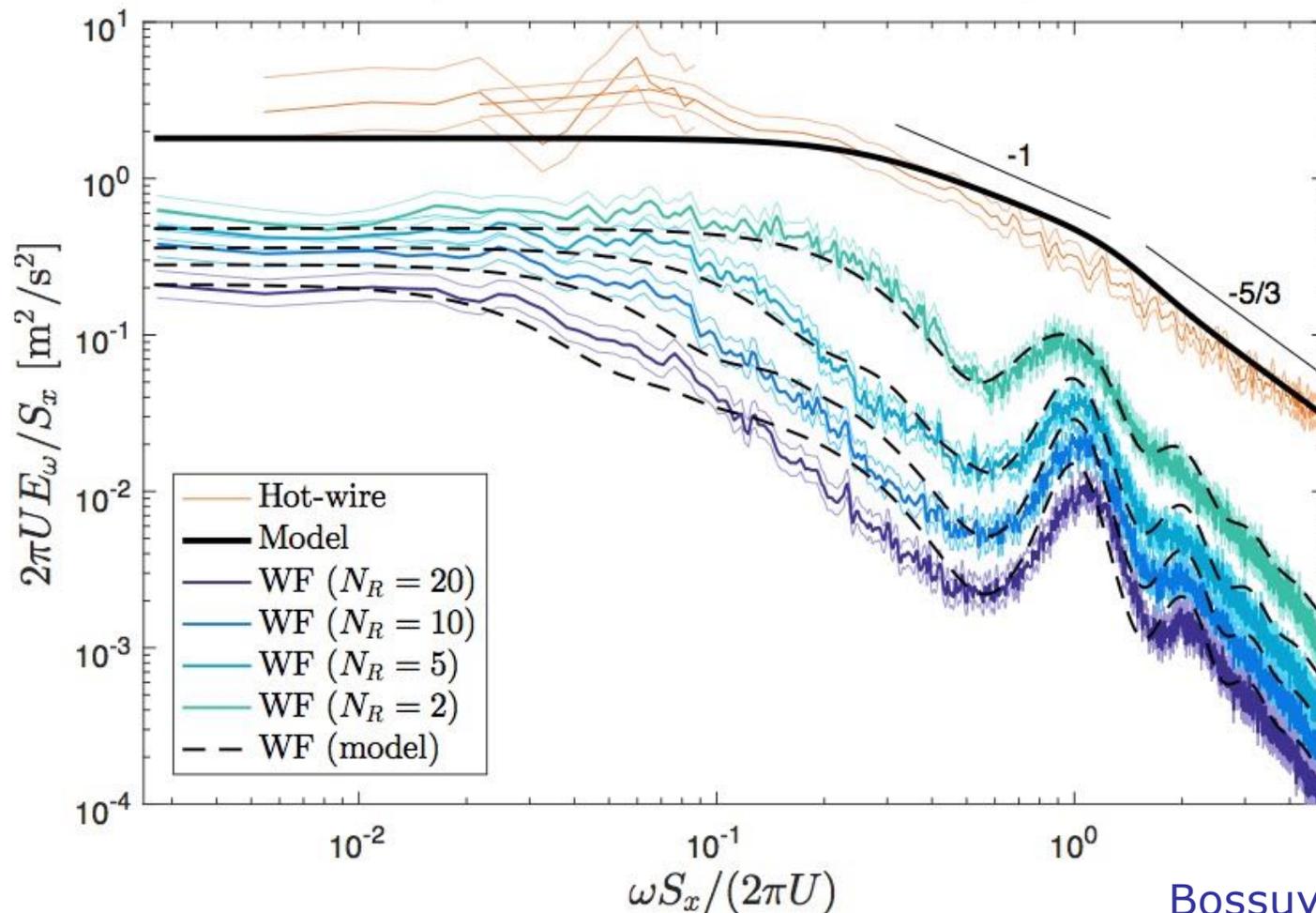
Model



# Comparisons of measured and model spectra

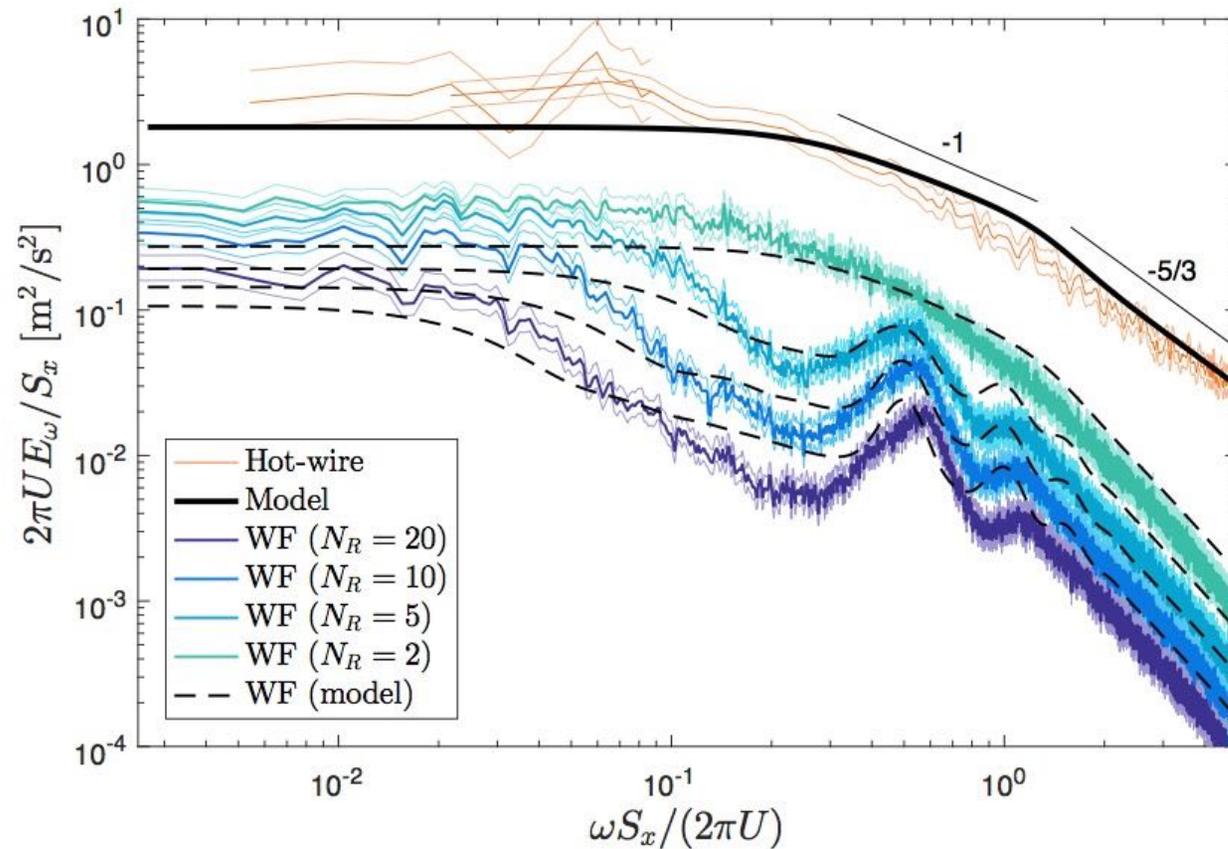
$$E_{P'}(\omega) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |\hat{g}(k_1, k_2)|^2 E_{11}(k_1, k_2, \omega, z_h) dk_1 dk_2$$

Aligned array (lines: data, dashed line: model)



# Comparisons of measured and model spectra

Staggered array (lines: data, dashed line: model)



$$E_{P'}(\omega) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |\hat{g}(k_1, k_2)|^2 E_{11}(k_1, k_2, \omega, z_h) dk_1 dk_2$$

**With this model, fluctuations can be included in cost function (e.g. power smoothing properties of various array configurations)**

# Closing:

- We are in the process of a major energy infrastructure shift –  
50% wind electricity in a few decades possible – must get it right
- LES provides unprecedented fidelity of complex processes  
(Dynamic model: “applied RNG method”, using scale-invariance)
- Still too expensive for design – not used routinely, even RANS
- At least we can provide simulation-informed simpler models  
(e.g. analytical or reduced dimension) to improve design/control tools

$$\frac{\ln(\delta/z_{0,lo})}{\ln(\delta/z_{0,hi})} \ln \left[ \left( \frac{z_h}{z_{0,hi}} \right) \left( 1 + \frac{D}{2z_h} \right)^\beta \right] \left[ \ln \left( \frac{z_h}{z_{0,lo}} \right) \right]^{-1} = \frac{1}{N_d} \sum_{k=1}^{N_d} \left[ 1 - 2a \left( \sum_{j \in J_{A,k}} \left[ 1 + k_{w,\infty} \frac{x_{T,k} - x_j}{R} \right]^{-4} \right)^{1/2} \right]$$

$$E_{P'}(\omega) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |\hat{g}(k_1, k_2)|^2 E_{11}(k_1, k_2, \omega, z_h) dk_1 dk_2$$

