

From wall measurements to three-dimensional turbulent-flow fields via GANs

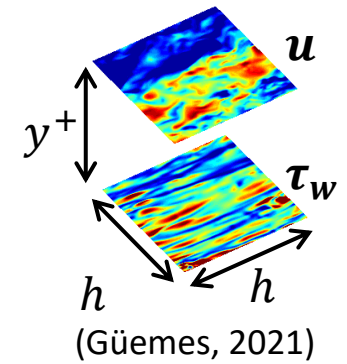
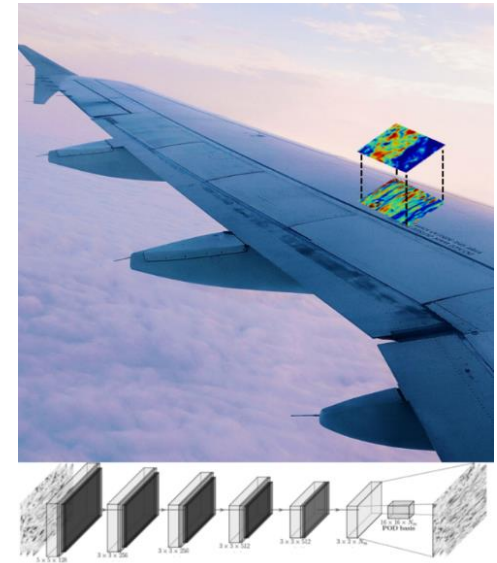
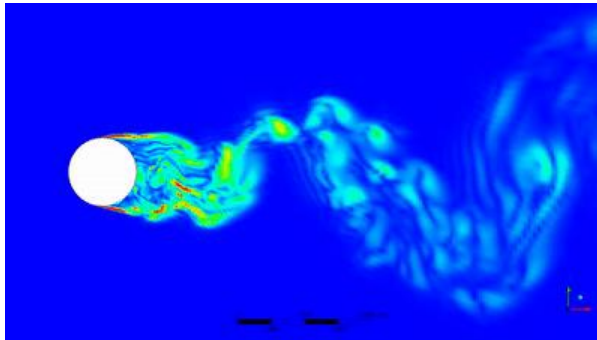
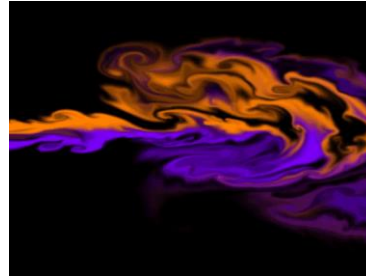
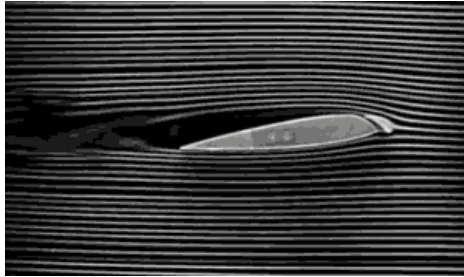
**A. Cuéllar¹, A. Güemes¹ A. Ianiro¹,
O. Flores¹, R. Vinuesa², S. Discetti¹**

¹ Aerospace Engineering Research Group (UC3M)

² FLOW, Engineering Mechanics (KTH)



Flow sensing from wall measurements

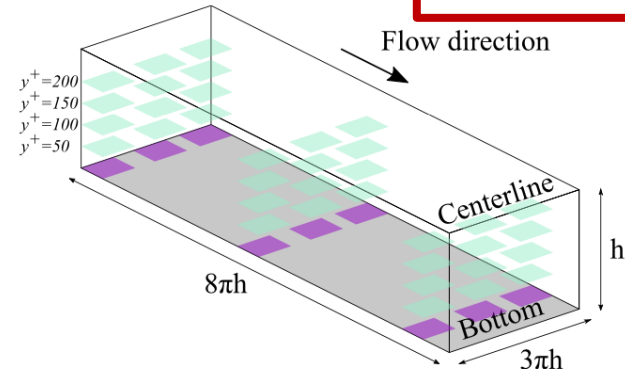


Flow sensing from the wall (ML)

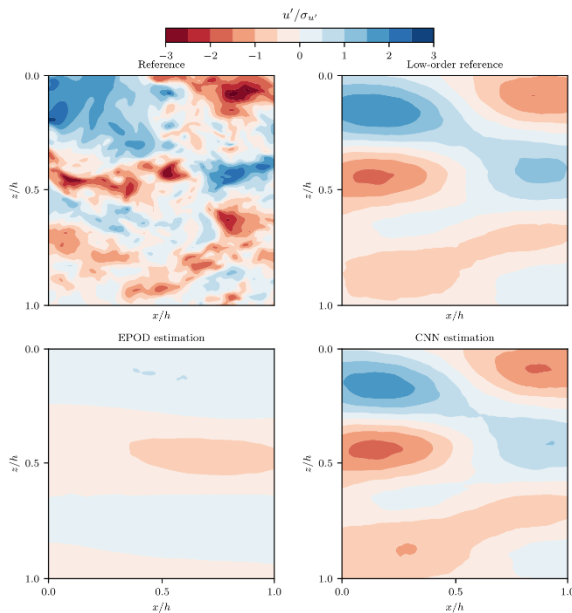
Estimation of fluid properties from wall quantities

- Linear methods
- Machine learning

One trained network for each wall-normal distance

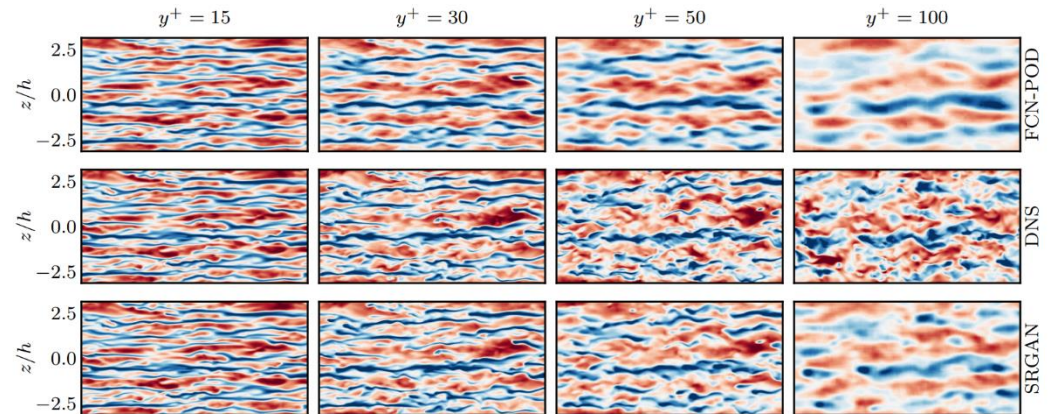


From Johns Hopkins Turbulent Data Base:
Channel Flow, $Re_\tau = 1000$



(Güemes, 2019)

From DNS (pseudo-spectral code):
Open channel Flow, $Re_\tau = 180$



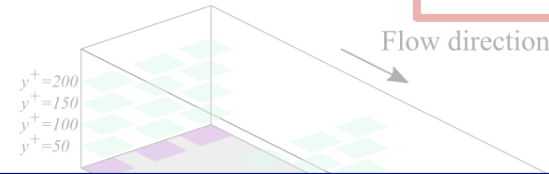
(Güemes, 2021)

Flow sensing from the wall (ML)

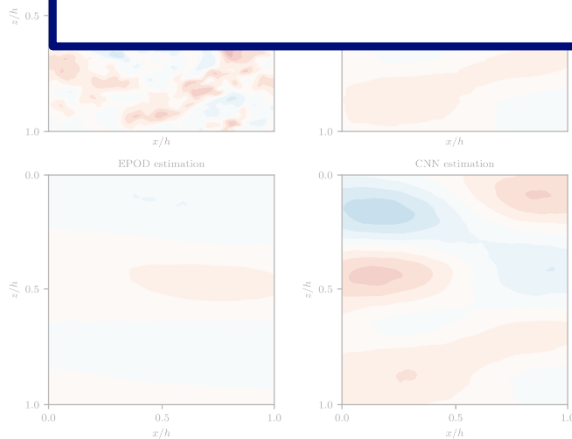
Estimation of fluid properties from wall quantities

- Linear methods
- Machine learning

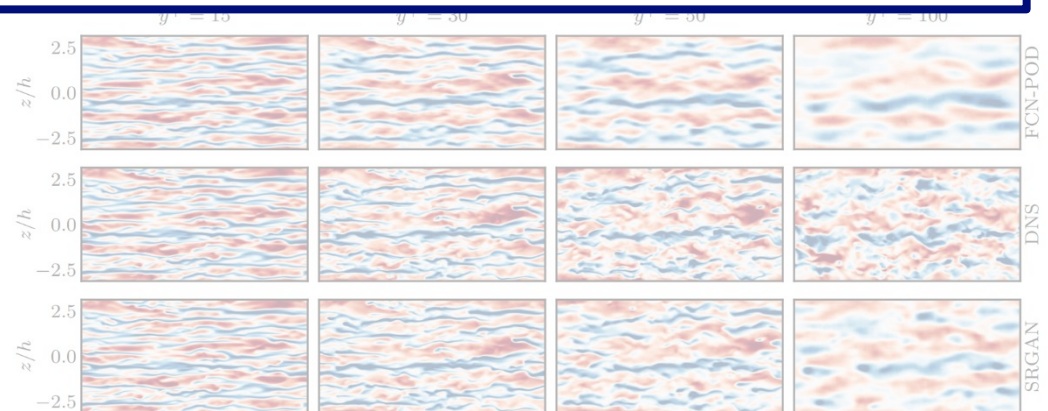
One trained network for each wall-normal distance



Is it possible to train a single architecture to obtain directly the full 3D estimation?



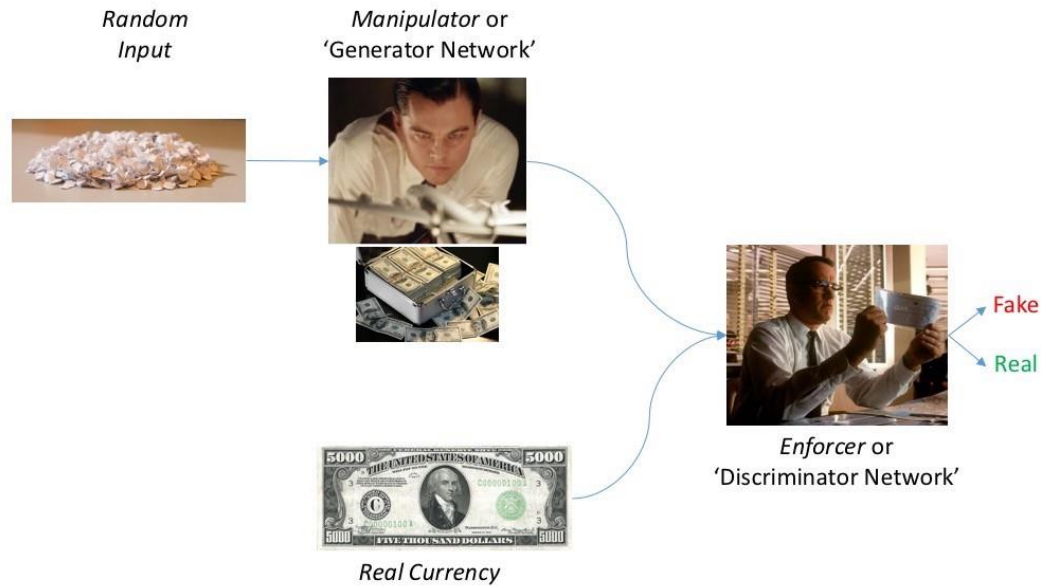
(Güemes, 2019)



(Güemes, 2021)

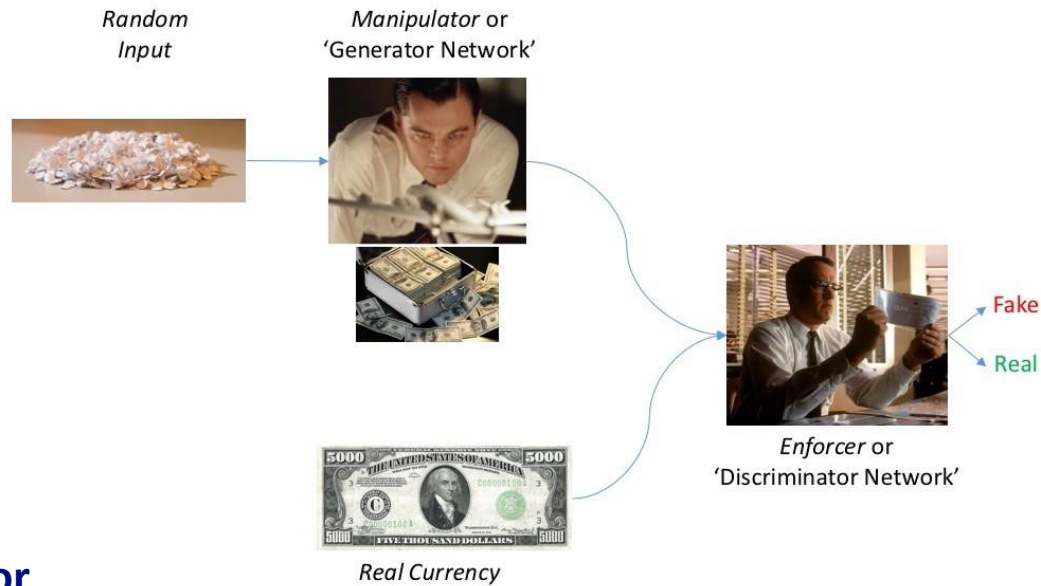
GANs: Generative Adversarial Networks

Example

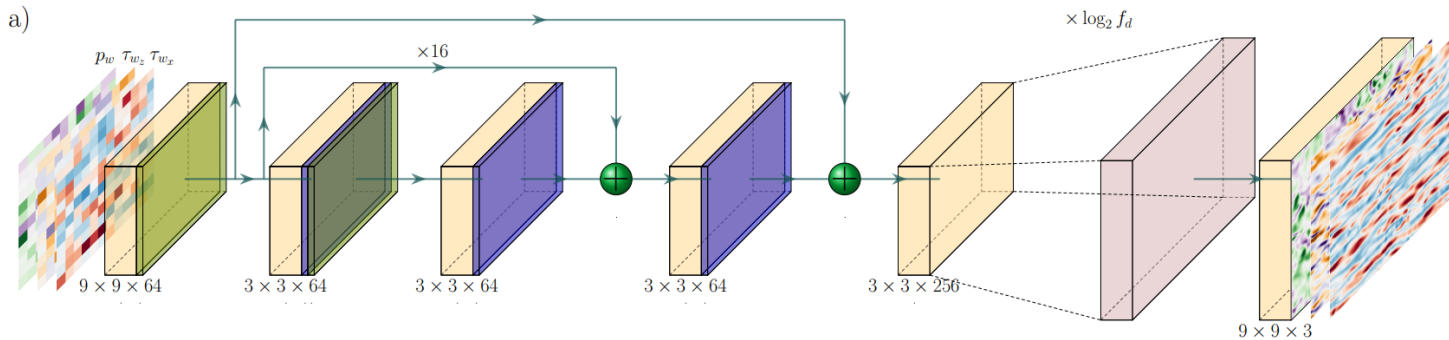


GANs: Generative Adversarial Networks

Example



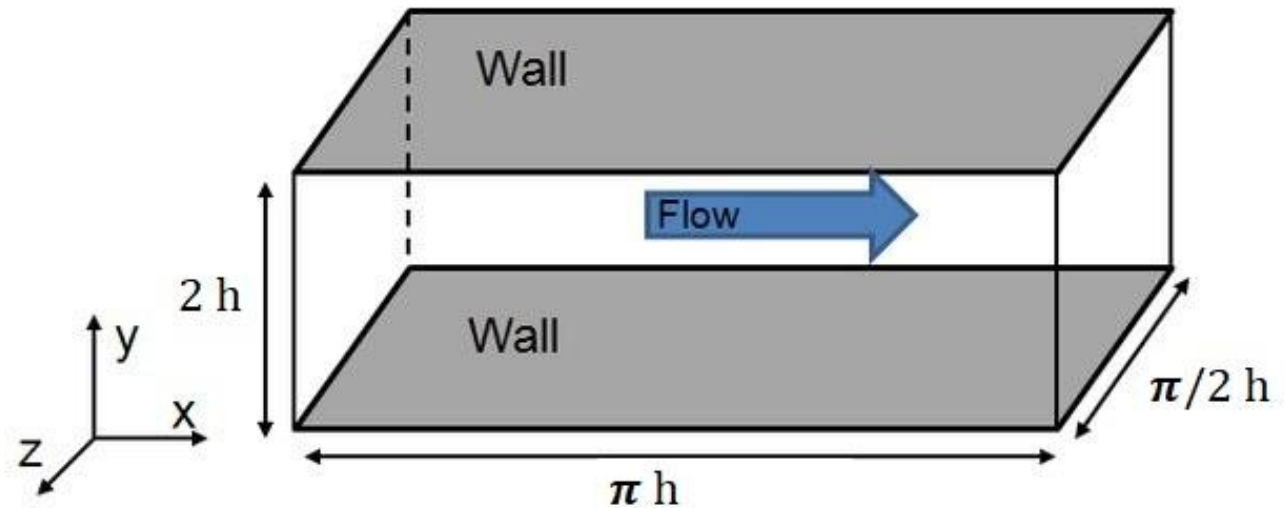
Generator



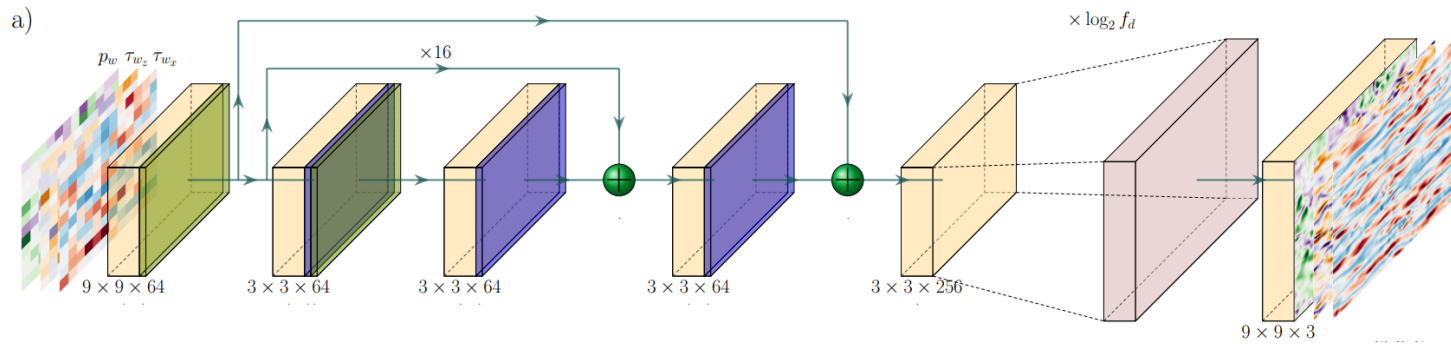
(Güemes, 2021)

The channel

- DNS database: **Turbulent channel flow**
- $Re_\tau = 200$
- $x [0 - \pi h]$, $y [0 - 2h]$, $z [0 - \frac{\pi}{2} h]$
- Points [64, 128, 64]

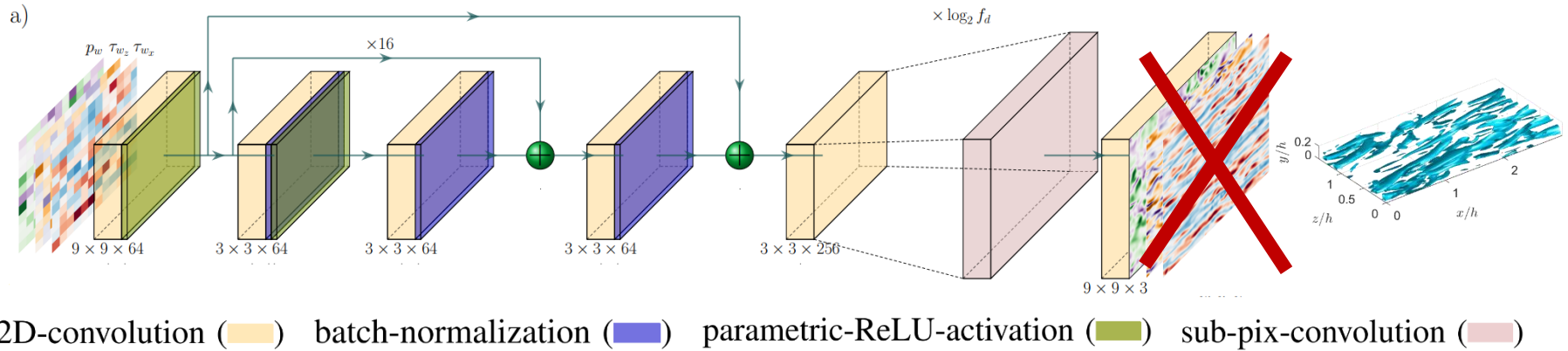


3D GAN

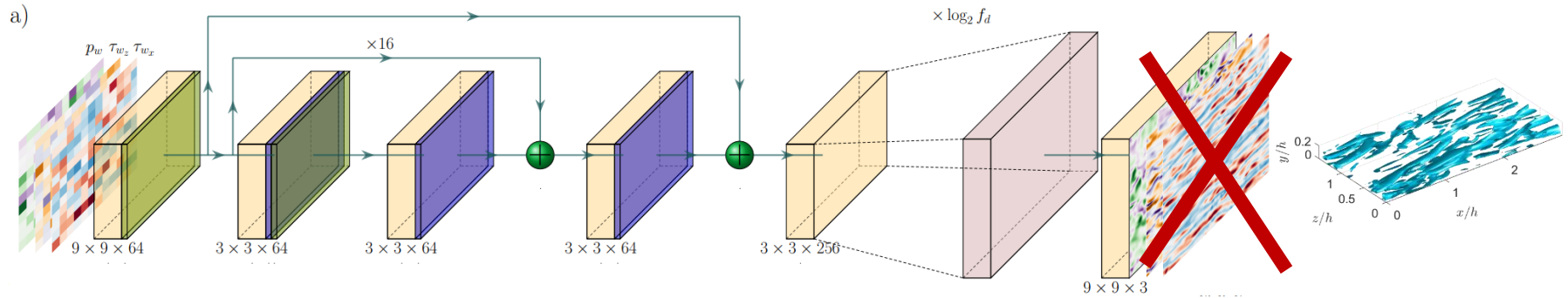


2D-convolution (yellow) batch-normalization (blue) parametric-ReLU-activation (green) sub-pix-convolution (pink)

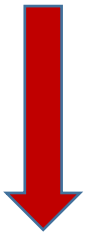
3D GAN



3D GAN

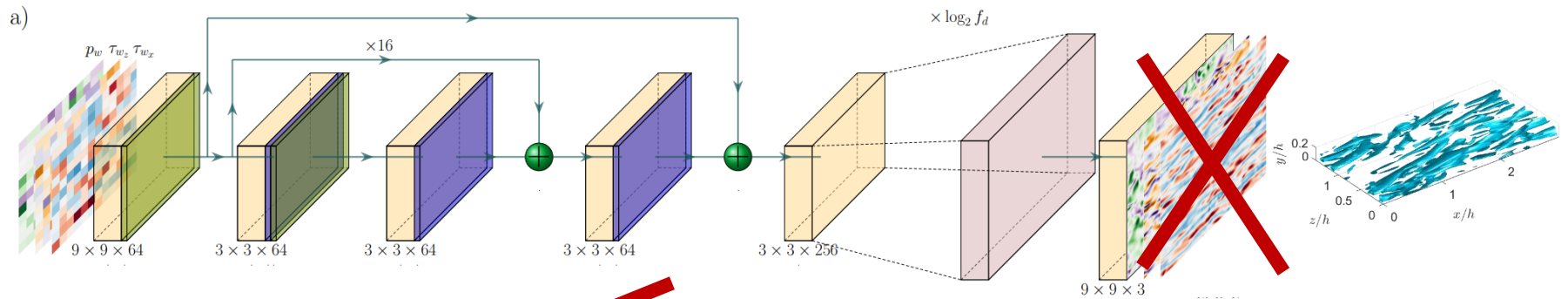


2D-convolution (yellow) batch-normalization (blue) parametric-ReLU-activation (green) sub-pix-convolution (pink)



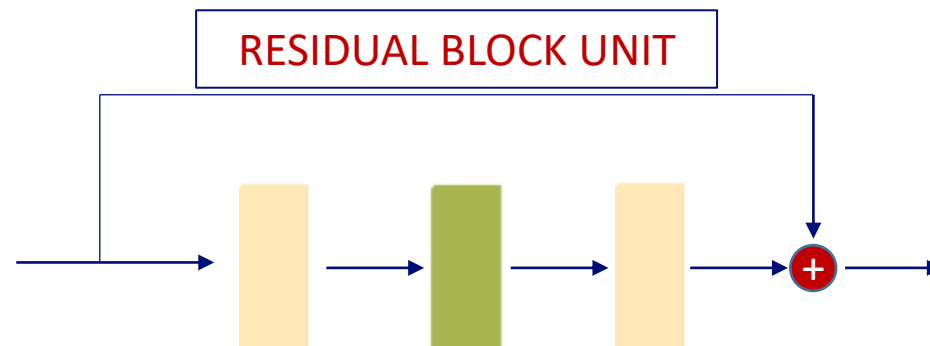
3D CONVOLUTION
LAYERS

3D GAN

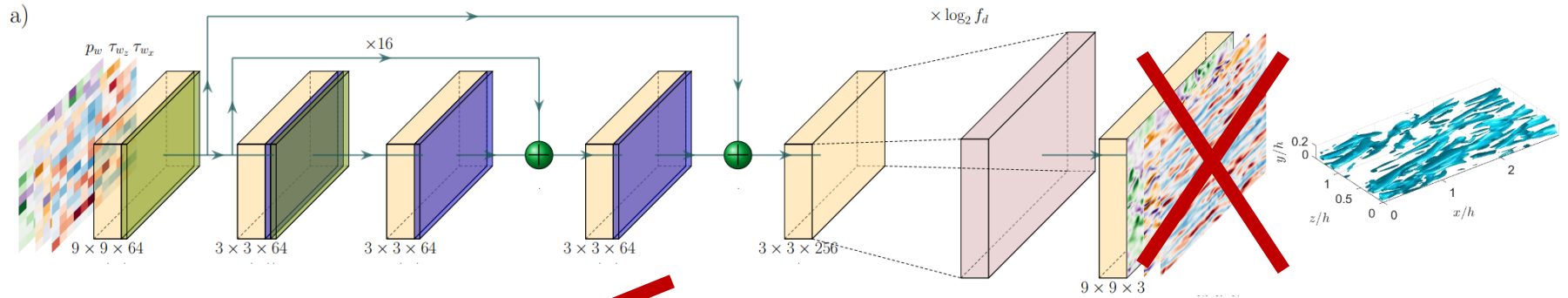


2D-convolution (yellow) batch-normalization (blue) parametric-ReLU-activation (green) sub-pix-convolution (pink)

**3D CONVOLUTION
LAYERS**



3D GAN

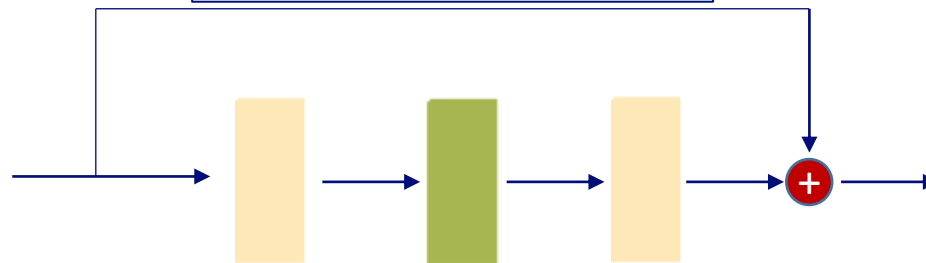


2D-convolution (yellow) batch-normalization (blue) parametric-ReLU-activation (green) sub-pix-convolution (pink)

3D CONVOLUTION LAYERS

RESIDUAL BLOCK UNIT

POSITION OF UP-SAMPLING LAYERS

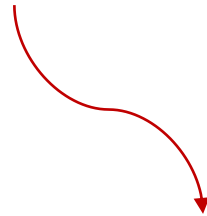


Flow sensing from wall-measurements

KEY ASPECTS

- Higher complexity, +1 dimension
- Computational power
- Number of trainable parameters

2D → 3D



[SNAPSHOT , X , Y , Z , FILTER]

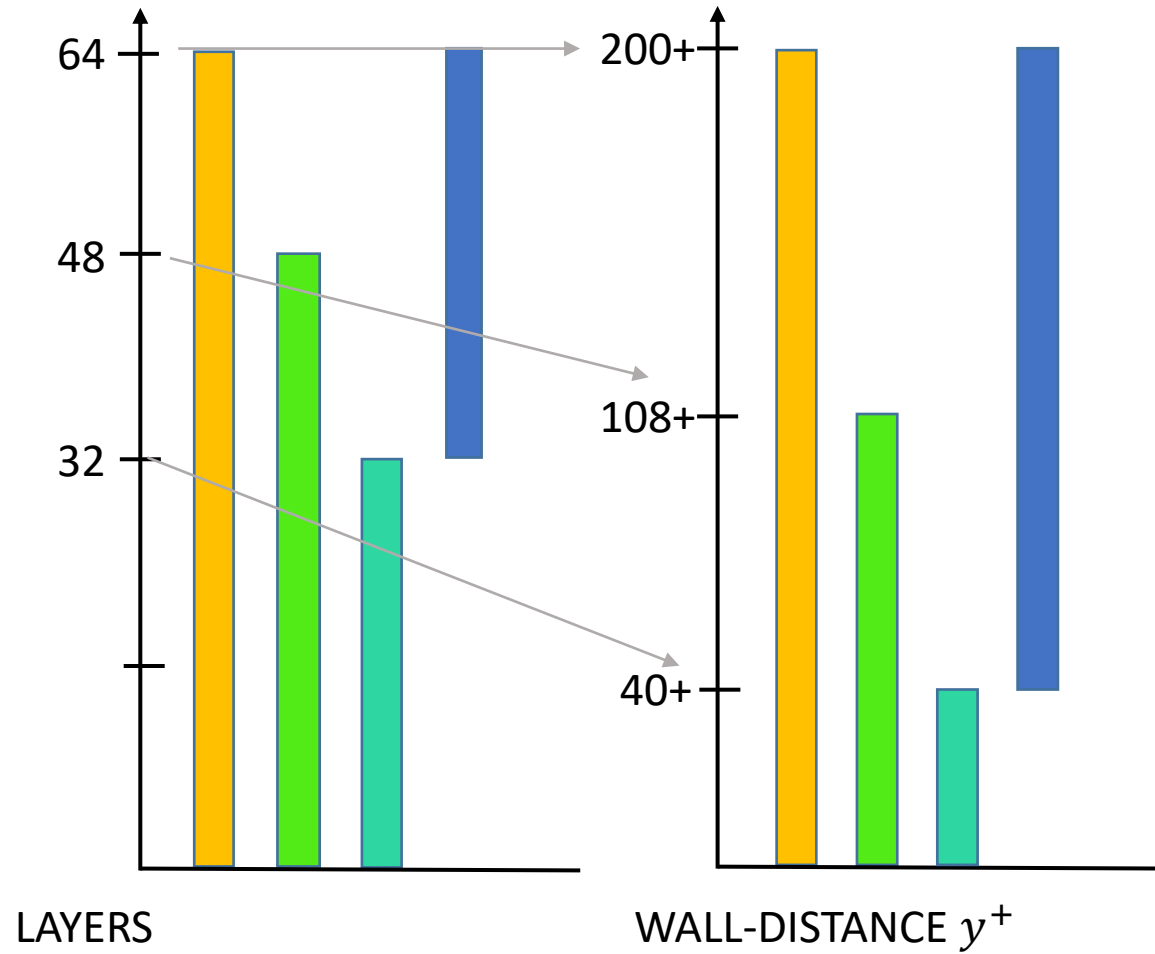
Results: CASES

A: 1 – 64

B: 1 – 48

C: 1 – 32

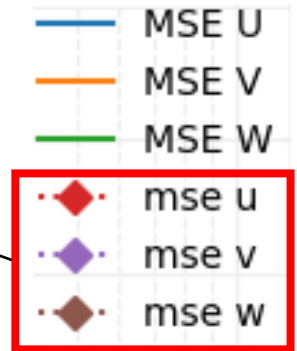
D: 33 – 64



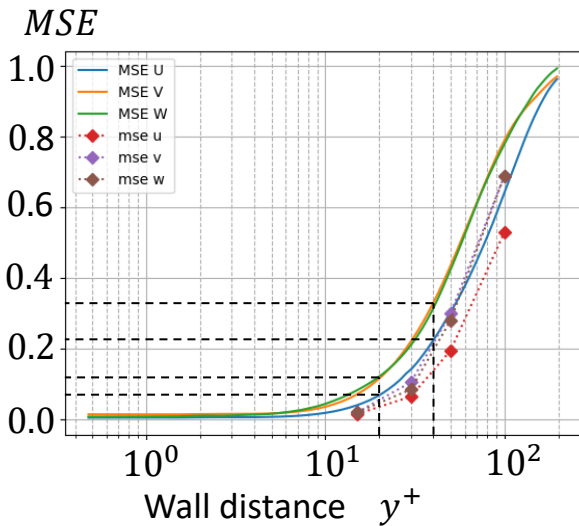
Results: CASES A, B, C

$$MSE = \sqrt{(a - a^*)^2}$$

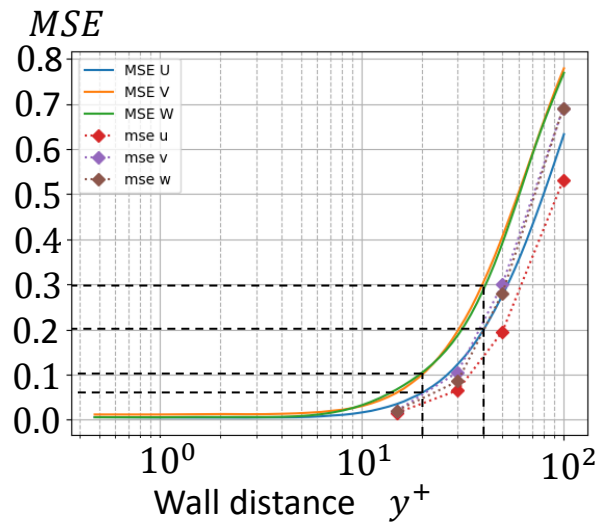
From Güemes *et al.* PoF 2021



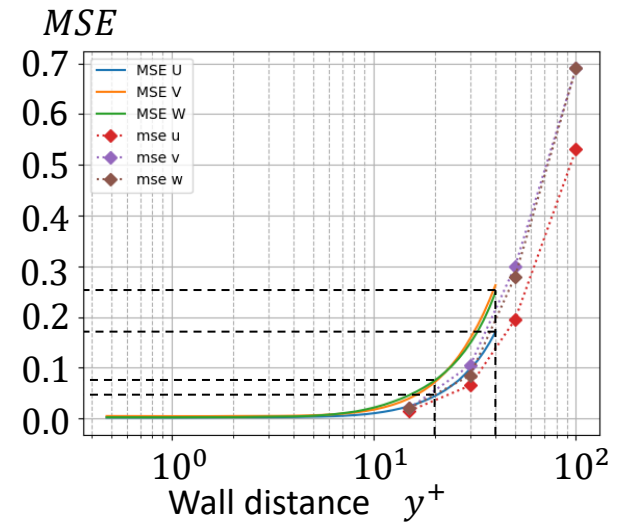
ERROR: A > B > C



A: 1 – 64



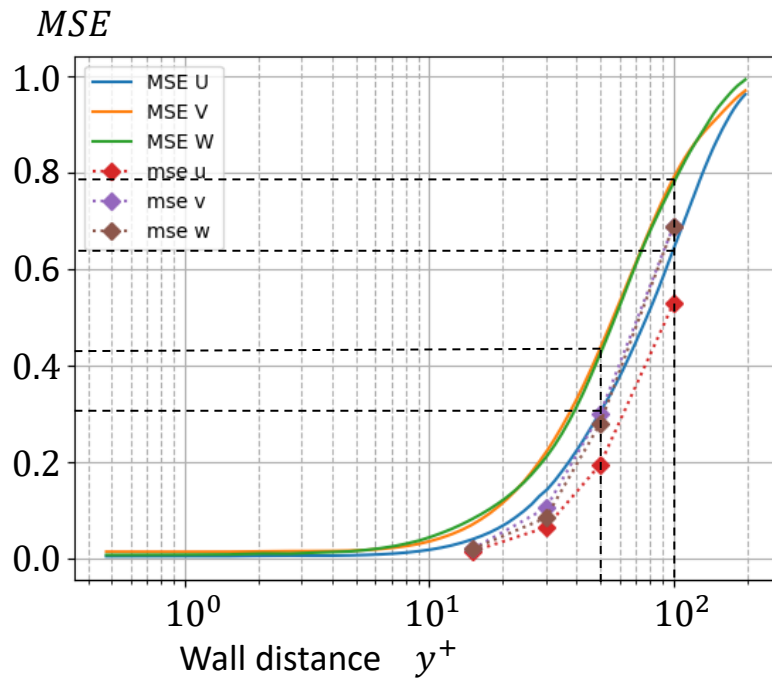
B: 1 – 48



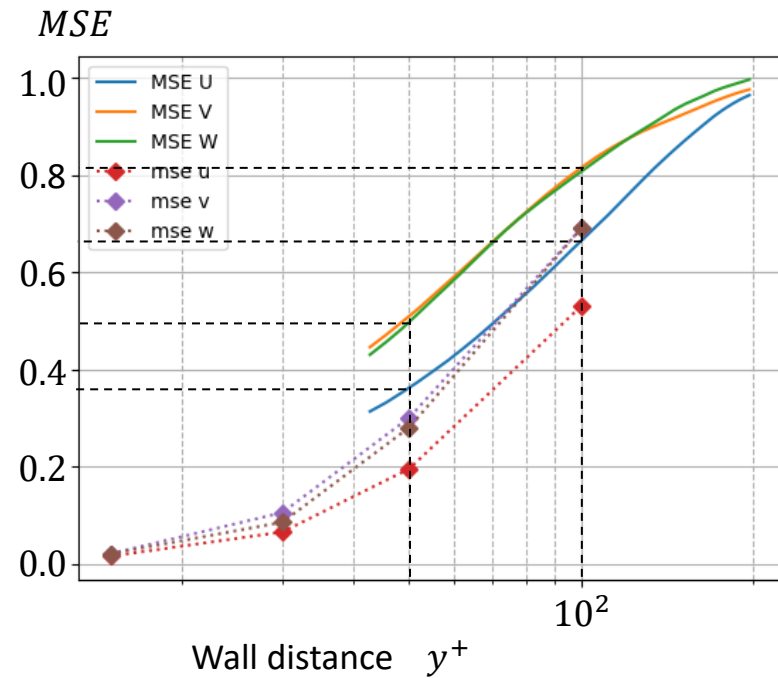
C: 1 – 32

Results: CASE D

$$MSE = \sqrt{(a - a^*)^2}$$



A: 1 – 64

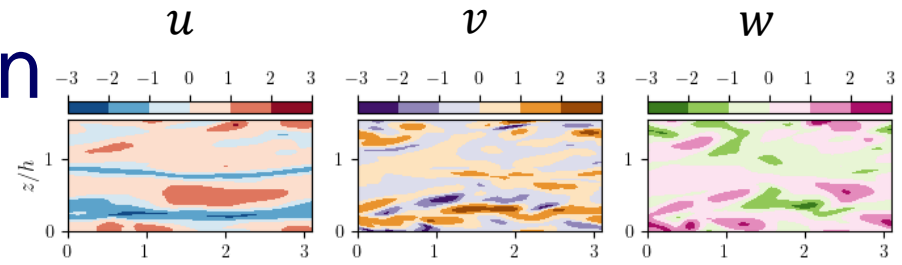


D: 33 - 64

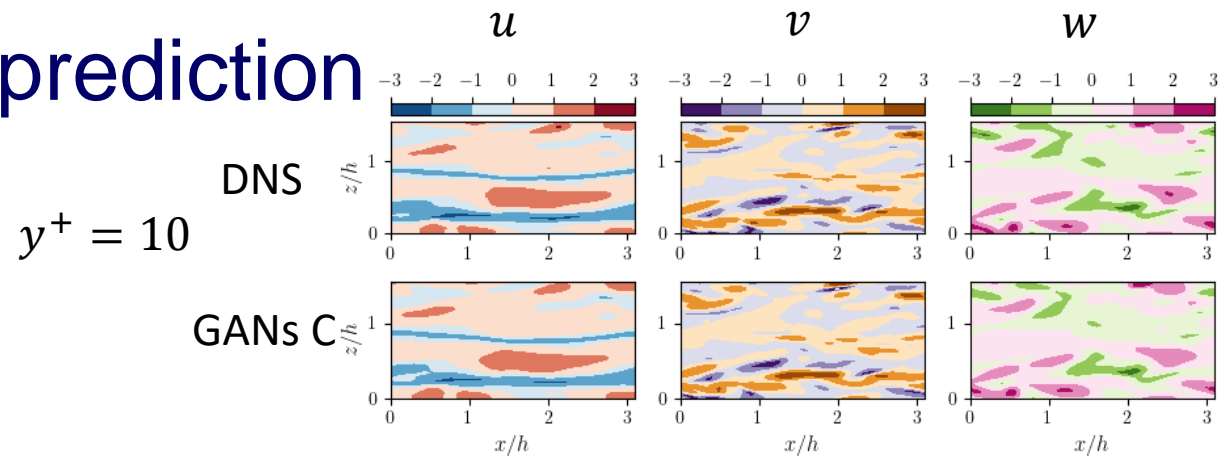
Results: Field prediction

$$y^+ = 10$$

DNS



Results: Field prediction



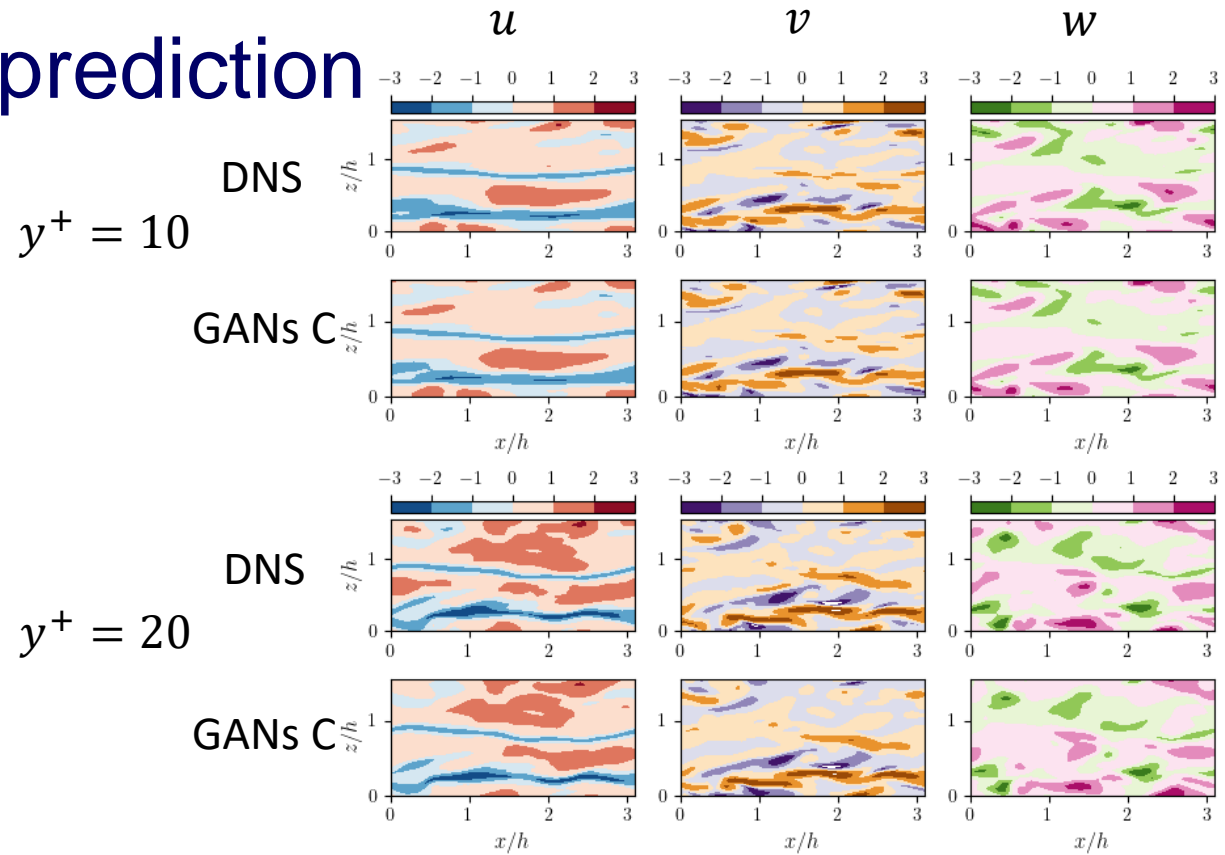
MSE

y^+	u	v	w
10	0.02	0.04	0.05

Results: Field prediction

MSE

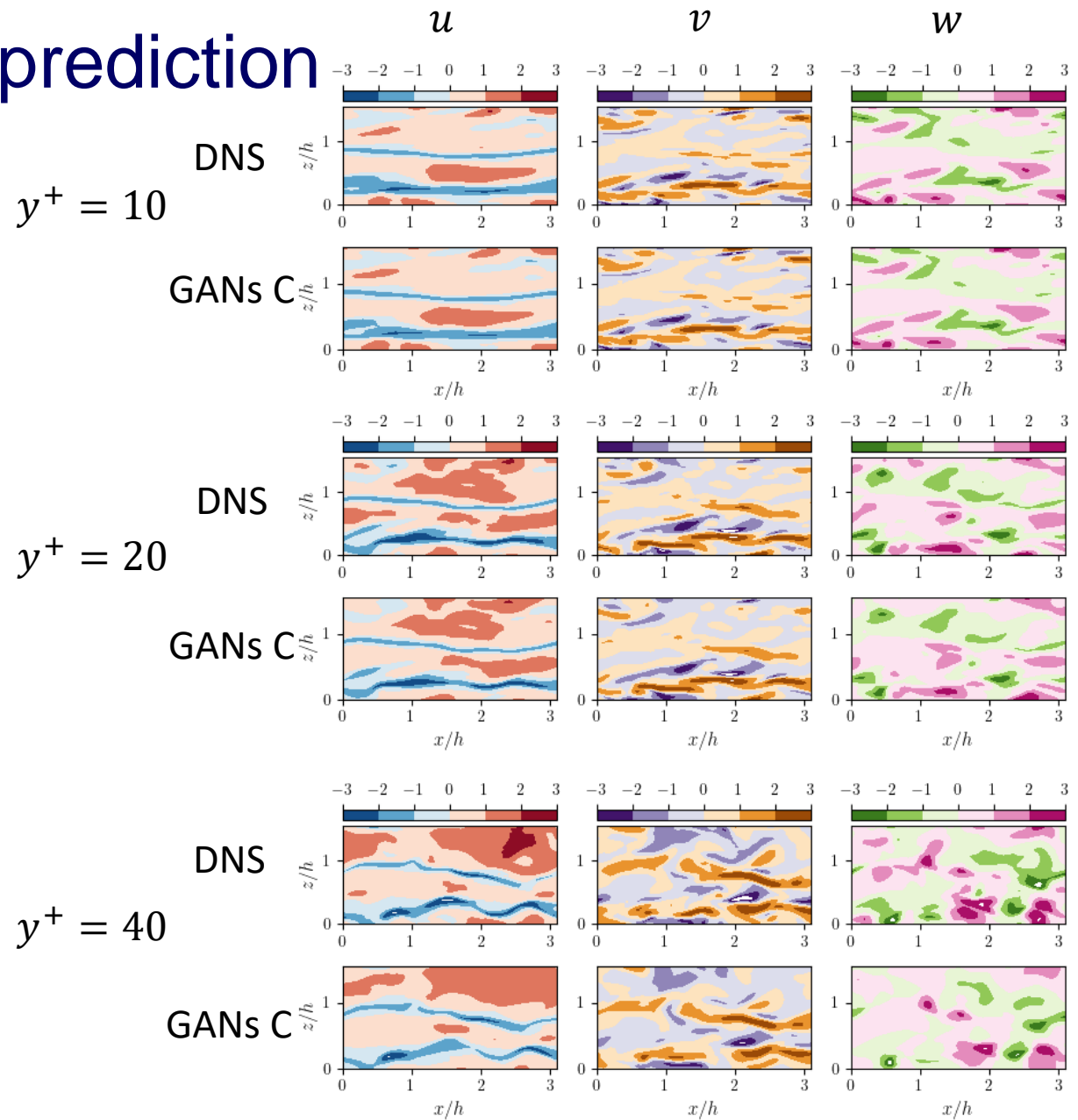
y^+	u	v	w
10	0.02	0.04	0.05
20	0.09	0.16	0.16



Results: Field prediction

MSE

y^+	u	v	w
10	0.02	0.04	0.05
20	0.09	0.16	0.16
40	0.17	0.26	0.26



Conclusions

- “One-shot” 3D estimation is feasible with small loss of accuracy with respect to multi-plane GANs
- The number of trainable parameters can be significantly less than in multi-plane GANs
- The network estimates wall-attached structures

THANKS FOR YOUR ATTENTION

THIS PROJECT HAS RECEIVED FUNDING FROM:

The Spanish Ministry of Universities under the Formación de Profesorado Universitario (FPU) program

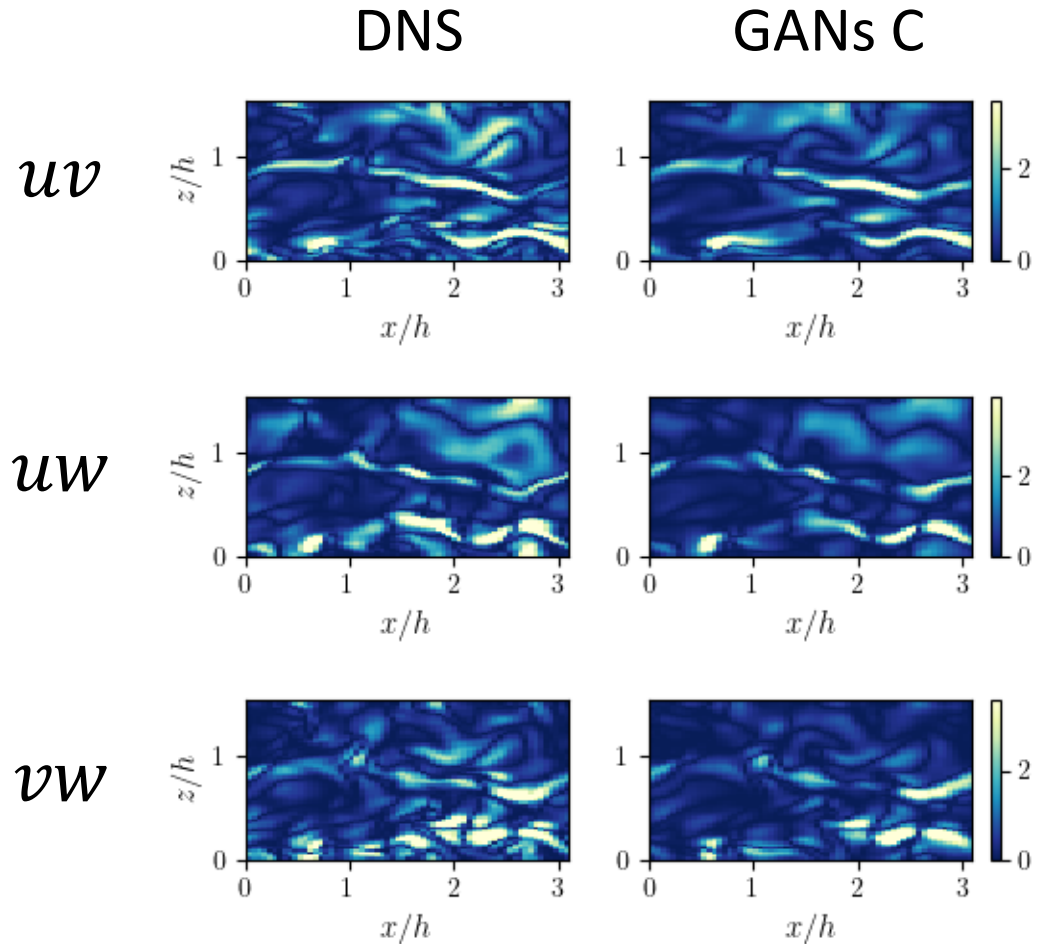


The European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation program (grant agreement No. 949085)



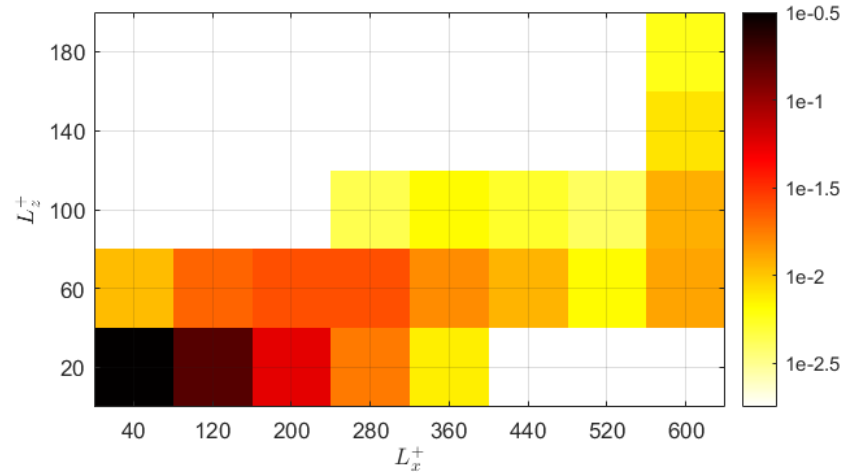
Results: Velocity component product

$$y^+ = 40$$



Results: Velocity component product

DNS



GANs C

